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OTTO KÄSSI

STUDIES ON EARNINGS DYNAMICS AND
UNCERTAINTY IN RETURN TO EDUCATION

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Otto Kässi

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Chapter 1

Introduction

1.1 Background

In their classic article, which was actually written in the 1940s but published in 1954, Friedman & Kuznets (1954) study a data set from a yearly survey administered by the U.S. Department of Commerce in the late 1920s and early 1930s. The survey concerned professional men practising their trade independently in five professions: engineering, accounting, law, medicine and dentistry. According to Friedman & Kuznets, their paper is a "detailed description of the income structure of [the] five professions". They study the inequality between and within each professional group, and how they evolve over time. One of their particular interests is something they call "the stability of relative income status", or, if the earnings inequality within a profession is mostly permanent or transitory.

These two types of earnings inequality have different implications for long-run earnings inequality. Permanent earnings differences imply inequality in the long run; high income professionals remain high income professionals and low income professionals remain low income professionals. Transitory inequality, on the other hand, implies shuffling within the earnings distribution; a high income professional may have low income in the next year, and vice versa. To disentangle permanent and transitory income differences from one another, researcher obviously needs a panel data set, where the same people are followed over consecutive years.

Many of the themes discussed in this thesis were systematically covered for the first time in Friedman & Kuznets (1954). Their paper is, to my knowledge,

the first empirical economics paper to utilize panel data in studying earnings differences between and within groups.¹

The analysis in Friedman & Kuznets (1954) might seem rather archaic to today's reader. Their analysis was limited by the lack of representative publicly available datasets and computational power in their disposal. In addition, the economic and statistical knowledge has significantly cumulated in the last 70 years. Nonetheless, many of the concepts and ideas first presented in their paper are still present in modern economic literature, including this doctoral thesis.

This thesis consists of three independent essays all related to earnings inequality and uncertainty. Chapter 2 is a descendant of Friedman & Kuznets (1954). It studies the earnings structure of two broad groups: working Finnish males and females and decomposes the variance of yearly earnings into two components, a transitory and a permanent effect. The estimation is done using a random sample from Finnish census covering years 1988-2007.

Friedman & Kuznets (1954) also compare the means and dispersions of the income of professionals to that of salaried workers. They find that professional workers earn substantially more than salaried workers, but they also note that the professional workers tend to come from affluent families (who can support their training) and practicing a profession requires long formal training, therefore "innate ability" of professionals may be higher than the innate ability of salaried workers. Based on this observation, they speculate that professionals might have earned more than average salaried workers even if they had decided not to pursue a profession. This is a classic example of selection bias (Heckman, 1979; Willis & Rosen, 1979).

Selection also affects the estimation of earnings uncertainty of different career choices. In particular, if people know their innate ability but the researcher does not have a sufficient measure for it, earnings variance of a certain profession group will overstate the uncertainty of that career. Chapters 3 and 4 of this thesis also provide estimates for monetary returns and uncertainty for a particular career choice, namely education, corrected for selection. In chapter 3, the main interest is returns to completing a degree and related uncertainty, whereas chapter 4 studies returns to university majors and their uncertainty.

¹Milton Friedman was later awarded the Nobel Memorial Prize in Economic Sciences partly for his work on how transitory income shocks translate to changes in consumption (see Friedman 1957).

1.2 Finnish registry data

All of the chapters of this thesis are empirical and they employ Finnish registry data. The main strength Finnish registry based data is its high quality. In particular, the earnings and income measures are calculated from filed tax reports so measurement errors due to misreporting are arguably very small. The downside of using income data derived from tax registries is that tax reports do not have any information on hours worked, which forces me to limit my attention to yearly income measure. All of the chapters in this thesis employ random samples of the true underlying population of all Finns, which ensures that the results can be reliably generalized to Finnish population.

The measure used in chapter 2 is annual labor earnings. This measure includes income from paid employment, but does not include income from entrepreneurship. The measure used in chapters 3 and 4 is the total income subject to taxation, which includes the the income from paid employment, taxable social security transfers, and entrepreneurial income. Neither of the two income concepts include income from capital goods.

To limit the attention to people who are a part of the workforce, I use the "main type of economic activity" indicator of individuals to classify them. The main type of activity of individuals is inferred by Statistics Finland by combining information from various registries. To be a part of the workforce, an individual has had to be either employed or unemployed for at least 6 months during a year, but it is entirely possible that people who are classified as "working" have faced spells of unemployment, or, vice versa, people who are classified as "unemployed" have done some work over the year.²

It might be possible, that large negative income shocks might force some people out of the workforce to be stay-at-home parents or students, which leads to a particular type of a selection problem. The wages of non-workers are virtually impossible to observe! This issue is present in some form or another in all of the chapters of this thesis, and, indeed, in a large part of the contemporary empirical labour economics literature. Nonetheless, since the unemployment benefits and most other income transfers are taxable, they are also observed in the data. Using an income measure which includes these income transfers arguably gives a more complete view on the income inequality

²For more information, see http://www.stat.fi/til/tyokay/kas_en.html (downloaded 2014-01-08).

and income risks prevalent in the society.

Most of the existing papers studying either of the above mentioned themes concentrate on working males and disregard females entirely. The underlying assumption is that the labour force participation of men is more or less constant whereas the labour force participation of women is jointly determined with other family decisions (e.g., fertility), which may, in turn, cause problems for the estimation. I depart from previous literature in all of the subsequent chapters of this thesis by estimating separate models for men and women. Since the labour force participation of women is very high in Finland, I see that calculating comparable measures for males and females is reasonable.

1.3 Permanent and transitory income differences

1.3.1 Related literature

Income inequality has grown in most of the industrialized countries since the 1970s. This has generated a demand for research which tries to describe the phenomenon and understand its underlying causes. A particular strand of this literature are studies on earnings dynamics, which decompose the distribution of earnings into their permanent and transitory components. This approach is also taken in chapter 2 of this thesis. I study the annual variance of earnings, decompose it into permanent and transitory components and study their evolution over time.

The two earnings components have different underlying causes. Permanent earnings differences are usually attributed to fixed worker attributes such as education, and skills which are relatively constant from the point of view of an individual. Transitory shocks, on the other hand, imply more volatile earnings and, consequently, shuffling of individuals and are typically attributed to worker turnover and other macroeconomic factors.

The two components may also have different implications for public policy. If a policymaker aims to decrease inequality in consumption and earnings differences are mainly permanent, the policymaker may want to implement policies which subsidize human capital investments of the most disadvantaged people. If the transitory shocks are relatively small, people will be able to smooth their consumption by saving. If, on the other hand, transitory earnings shocks are large or very persistent, the policymaker might want to educate

the public about risk-sharing instruments provided by insurance companies, and credit or stock markets.

Chapter 2 of this thesis is influenced by a series of paper studying the same question. Early work studying the same concepts and using similar terminology is the already mentioned Friedman & Kuznets (1954), but their paper does not actually quantify the contribution of the permanent and transitory components. Later, Lillard & Weiss (1979) and Hause (1980) applied the same conceptual framework to test if the evolution of permanent earnings differences are consistent with a so-called "on-the-job training hypothesis"³.

The first papers to plausibly describe the income distribution prevalent in the society using nationally representative samples include MaCurdy (1982), Baker (1997), and Haider (2001), all of which use data from the U.S. A similar decomposition has also been presented, for example, for Canada (Baker & Solon, 2003), the U.K. (Ramos, 2003) and Italy (Cappellari, 2004).

The focus of aforementioned papers is mostly in describing the key properties of earnings distribution. More recently they have also been used as building blocks in macroeconomic models which aim to study how income shocks affect consumption, savings and wealth accumulation (e.g. Blundell et al. 2008 and Guvenen & Smith 2010).

1.3.2 Earnings Dynamics of Men and Women in Finland: Permanent Inequality versus Earnings Instability

Even though there are a multitude of papers fitting variants of the same model, there are differences in model specifications, data construction and also the results⁴. Replicating the analysis using data from a new country is therefore warranted.

Chapter 2 is a descriptive econometric study on earnings distribution in Finland. It presents a decomposition of earnings inequality into its perma-

³According to the on-the-job training hypothesis, individuals may accept lower earnings at the beginning of their career, if they anticipate that their earnings will rise at a high enough rate and for a long enough time to compensate for low earnings at the beginning of their career. This implies that the covariance of earnings growth and initial earnings will be negative (Mincer, 1974).

⁴As a case in point, Dahl et al. (2011) report that different public use data sets from the U.S. give quantitatively different results on the evolution of earnings inequality over the same time period.

nent and transitory components and studies their evolution through time and variation between cohorts.

The model presented is estimated by matching the theoretical moments implied by an econometric model to those calculated from observed earnings data. The estimation is done using the Equally Weighted Minimum Distance Estimation (EWMD) of Chamberlain (1984). Intuitively, the decomposition is identified using the sample autocorrelation of the earnings of individuals. For example, if the correlation between two adjacent years' earnings is found to be small, this implies that the transitory earnings differences dominate the permanent. If, instead, there is a high correlation between two adjacent yearly observations, permanent income inequality will likely dominate the transitory inequality.

The main result of chapter 2 is that the increasing earnings inequality is driven by both, permanent and transitory components, but their contribution is different for men and for women. For men, permanent inequality dominates the transitory inequality. For women, they are of similar magnitude. In addition, permanent earnings differences vary substantially between cohorts. Male cohorts are less equal in terms of their permanent earnings compared to women. There has also been a trend increase in earnings instability of both sexes during the observation period. Further, accounting for both year and cohort specific differences in the estimation makes a difference.

The findings presented in chapter 2 suggest that if researchers only concentrate on males in their work, they may miss potentially important aspects of the earnings dynamics prevalent in the labour market.

1.4 Uncertainty in return to education

Monetary returns of education are one of the most widely studied topics⁵ in empirical microeconomics⁵, but the dispersion of these returns has gotten much smaller empirical attention. The topic also has some policy relevance since education is often promoted as an insurance against earnings risk, but the empirical evidence is mixed at best.

This section proceeds by presenting a simple model which is used to introduce the setup and terminology used in chapters 3 and 4. The setup is adapted

⁵Therefore, it is not surprising that other methods, besides the one discussed here, have been presented in recent literature. For reviews, see Card (2001) and Blundell & Dias (2009).

from Willis & Rosen (1979).

1.4.1 A simple model

Assume that the income of an agent is given by

$$\begin{cases} y_{0i} = \alpha + \varepsilon_{0i}, & \text{if } S_i = 0, \\ y_{1i} = \alpha + \delta S_i + \varepsilon_{1i} & \text{if } S_i = 1. \end{cases} \quad (1.1)$$

where S_i is a binary variable measuring the level of education ($S_i = 0$ if the agent is an upper secondary school graduate and $S_i = 1$ if the agent has a university degree). ε_{0i} and ε_{1i} are two zero-mean error terms related to education levels. Now, if S_i was independent of $(\varepsilon_{0i}, \varepsilon_{1i})$, estimating the return to getting a higher level of education and the associated variance would be simple. The expected value for return to education would simply be δ and the variances of earnings for the two education groups would simply read as $Var(\varepsilon_0)$ and $Var(\varepsilon_1)$.

A particular example where the independence of schooling choice and disturbance terms might not hold, is the latent utility formulation

$$S_i = I[\nu_i \geq 0], \quad (1.2)$$

where ν_i is another random variable, "taste for education", which summarizes ability, parental example and other characteristics of agents which affect schooling choices but are not observable to the researcher. $I[\cdot]$ is an indicator function which has a value of 1 if $\nu_i \geq 0$ and 0 otherwise.

Combining Equations (1.1) and (1.2) gives the expression for the expected value for the income of the subgroup where $S_i = 1$

$$E[y_1] = \alpha + \delta S_i + E[\varepsilon_1 | S_i = 1]. \quad (1.3)$$

The estimate for the return to education, δ , will be biased if the last term in Equation (3) is non-zero. This occurs if, for example, more skilled individuals choose $S_i = 1$, but they might also earn more if they had chosen $S_i = 0$. This equivalent to $cov(\varepsilon_1, \nu) \neq 0$. The previous discussion is an example of the "sample selection bias as omitted variable bias" analysis discussed in Heckman (1979).

The empirical model outlined above imposes assumptions about the information set of the agents and the timing of events. The agents observe their

draw of ν_i and choose their level of education accordingly in the first period. It is further assumed that agents have full knowledge of the parameters governing the potential earnings, including the variances of ε_0 and ε_1 and the expected values of ε_{0i} and ε_{1i} conditional on ν_i , but the actual draws of ε_{0i} and ε_{1i} are only revealed in the second period after the choice of education has been made.

The residual variances of Equation (1.1) read as:

$$\begin{aligned} \text{Variance of } y_i \text{ given } S = 0 & \quad \text{var}(\varepsilon_0 \mid S_i = 0), \\ \text{Variance of } y_i \text{ given } S = 1 & \quad \text{var}(\varepsilon_1 \mid S_i = 1). \end{aligned}$$

These variances are comprised of two parts, the true uncertainty (unknown to the agents) and unobserved heterogeneity known to (and acted on by) the agents. The uncertainty faced by the agents reads as⁶

$$\begin{aligned} \text{Uncertainty of } S = 0 & \quad \text{var}(\varepsilon_0 \mid \nu, S_i = 0), \\ \text{Uncertainty of } S = 1 & \quad \text{var}(\varepsilon_1 \mid \nu, S_i = 1). \end{aligned}$$

Consistent estimation of the model outlined in Equations (1.1) and (1.2) requires constructing a regression with a mean-zero error term. The estimation generally requires an instrumental variable, z , which affects the selection into education, but has no effect on earnings after graduation.

If an instrumental variable is available, the estimation can be done in two stages. In the first stage, the probability of an agent choosing $S_i = 1$ conditional on z is estimated. In the second stage, an additional correction term which captures $E[\varepsilon_1 \mid S_i = 1, z]$, or the expected value of the error term conditional on the education choice made and the instrument. For example, many researchers who study returns to college in the U.S. use tuition costs at local colleges as instruments. The underlying assumption is, that of the two individuals with the same innate ability (i.e., the same draw of ν), the one living in an area with low tuition costs is more likely to attend a college.

The formulation of the correction term depends on the assumptions made about the joint probability distribution of the triple $(\varepsilon_0, \varepsilon_1, \nu)$. For instance, under the assumption that $(\varepsilon_0, \varepsilon_1, \nu)$ is jointly normal, the correction term

⁶The dispersion in return to education and uncertainty is discussed, among others, in Aakvik et al. (2010); Chen (2008); Cunha & Heckman (2007, 2008); Cunha et al. (2005) and Mazza et al. (2011).

reads as

$$\begin{aligned} E[\varepsilon_0 \mid S_i = 0] &= \text{cov}(\varepsilon_0, \nu) \times \text{var}(\varepsilon_0) \times \frac{-\phi(\gamma z)}{\Phi(\gamma z)} \quad \text{if } S_i = 0, \\ E[\varepsilon_1 \mid S_i = 1] &= \text{cov}(\varepsilon_1, \nu) \times \text{var}(\varepsilon_1) \times \frac{\phi(\gamma z)}{\Phi(\gamma z)} \quad \text{if } S_i = 1, \end{aligned}$$

where $\phi(\cdot)$ is the standard normal probability density function and $\Phi(\cdot)$ is the standard normal cumulative density function.⁷

The correction terms retain the assumption that the compound error terms $\eta_0 = \varepsilon_0 - \text{cov}(\varepsilon_0, \nu) \times \text{var}(\varepsilon_0) \times \frac{-\phi(\gamma z)}{\Phi(\gamma z)}$, and $\eta_1 = \varepsilon_1 - \text{cov}(\varepsilon_1, \nu) \times \text{var}(\varepsilon_1) \times \frac{\phi(\gamma z)}{\Phi(\gamma z)}$ have the expected value of zero even under self selection. Further, the residual variances explained by the bias correction term give an estimate for the unobserved heterogeneity.

Further, because unobserved heterogeneity affects the agents' education choice, the realized cross-sectional dispersion of income is effectively a truncated distribution, which means that observed wage inequality understates the potential wage inequality for a given level of education. Or,

$$\begin{aligned} \text{var}(\varepsilon_0) &> \text{var}(\varepsilon_0 \mid S_i = 0), \\ \text{var}(\varepsilon_1) &> \text{var}(\varepsilon_1 \mid S_i = 1). \end{aligned}$$

Intuitively this means that the uncertainty faced by the agents differs from the uncertainty we would observe if the education was randomly assigned to individuals.

The aforementioned exposition is somewhat simplified. In particular, in addition to the unobservable schooling factor, the models featured in chapters 3 and 4 allow people to differ in their observable characteristics by controlling for age, year of birth, school grades, and a variety of family background characteristics. Further, similarly to chapter 2, I differentiate between permanent and transitory earnings shocks using the panel dimension of the data.

⁷Vella (1998) surveys various parametric and semi-parametric models for selectivity correction. These models typically imply different functional forms of the correction term.

1.4.2 Uncertainty and Heterogeneity in Returns to Education: Evidence from Finland

Chapter 3 of this thesis studies the uncertainty related to different education levels using a broad measure of income which encompasses unemployment risk. The earnings measure used in the chapter is total yearly taxable income, which, in addition to wages, includes unemployment benefits and other taxable income transfers. This gives a possibility also to include the unemployed in the estimation allowing for a more complete picture of income uncertainty. The measure of uncertainty used in this chapter is the potential variance of earnings after correcting for unobserved heterogeneity and truncation.

The chapter studies two interrelated decompositions of the variance of earnings within an education group. First, unobserved heterogeneity and uncertainty are disentangled from one another using a selection correction model with jointly normal unobservable shocks. The uncertainty is further decomposed into permanent and transitory parts using the panel dimension in the data. The education level is measured as a four-valued ordered categorical variable which captures the salient features of the Finnish educational system. The categories are: compulsory education, secondary education (both vocational and upper), lower tertiary education and university level education.

To ensure that the schooling and income equations are jointly identified, I use local differences in supply of education proxied by the region of residence in youth as an instrument. Estimation results suggest that even after controlling for selection, education is a good investment: it brings higher mean earnings and smaller earnings shocks. Moreover, the income processes of men are riskier than those of women. The higher male income variance is largely driven by permanent earnings differences; no differences in unobserved heterogeneity are found. In addition, transitory shocks affect both genders and almost all education groups symmetrically. Only men in the lowest education category face larger transitory earnings shocks. The estimates on share of unobserved heterogeneity in permanent income differences are very small for both sexes and all education levels.

1.4.3 How Risky Is the Choice of a University Major?

Chapter 4 studies the earnings uncertainty of different majors. Analogously to chapter 3, earnings are measured by total yearly taxable income and un-

certainty is measured by the ex ante variance of yearly earnings. The analysis concentrates on a group of people who have both completed their upper secondary school degree and graduated from a university sometime in the 1990s or early 2000s. Since the latest data available is from year 2006, the results can be seen as reflecting early career income uncertainty.

For computational purposes, the majors are pooled into five roughly similar categories which are humanities, education and social sciences, law, business, engineering and natural sciences, and health. Contrary to chapter 3, the selection correction model is an unordered multinomial one and is adopted from Lee (1983). The selectivity of each major measured by the ratio of starting places to applicants is used as a supply-side instrument for major selection. The assumption is that, two similar individuals who face different entry requirements to majors will end up choosing different major subjects.

The effect of completing an academic degree is found to range between 104 and 169 for men and between 92 and 129 log points for women over the earnings of an upper secondary education. In addition to increasing expected returns, university education also is found to decrease earnings uncertainty for both sexes. The differences in mean earnings between academic fields are found to be statistically significant at 5% risk level, whereas the confidence intervals for the uncertainty estimates of different fields are mostly statistically indistinguishable from one another. As in chapter 3, the unobserved heterogeneity estimates are found to be very small.

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Chapter 2

Earnings Dynamics of Men and Women in Finland: Permanent Inequality versus Earnings Instability¹

Abstract

I decompose the earnings variance of Finnish male and female workers into its permanent and transitory components using the approach of Baker (1997) and Haider (2001) in the spirit of scientific replication.

I find that the increasing earnings inequality of men and women is driven by both the transitory and permanent components of earnings. In addition, I find considerable differences in the earnings dynamics of men and women, that have been largely neglected in previous studies of earnings dynamics. The inequality among men is dominated by the permanent component. Conversely, permanent and transitory components are of comparable magnitudes to women. As a corollary, men experience more stable income paths but display larger permanent earnings differences. Women, on the other hand, face more unstable earnings profiles but show smaller permanent differences in earnings.

¹A paper based on this chapter is published as Kässli (2014)

2.1 Introduction

Growing earnings inequality has been a common phenomenon to most of the developed countries since the 1970s and the need to understand this phenomenon has spurred a great deal of research.

Traditional studies of earnings inequality in Finland, as well as in other countries, have concentrated on measuring cross-sectional earnings inequality and its annual changes. However, concentrating on cross-sectional inequality hides an important element of economic inequality, namely the level of mobility of individuals within the earnings distribution.

More recent studies on earnings dynamics stress the importance of decomposing earnings inequality into its permanent and transitory parts. These two components have a different impact on long-term income differences and consequently have different welfare implications. If the rise in annual income inequality is driven by the transitory component, it suggests that earnings have become more volatile. This, in turn, may lead to a decrease in welfare, if individuals are unable to completely smoothen out income fluctuations. This might happen if earnings shocks are either very large or very persistent. On the other hand, if the rise in annual income inequality is due to fixed worker attributes, it implies that there is also increased inequality in career earnings. If the annual income inequality is driven by the transitory component, we should observe more year-to-year mobility within income distribution. This would lead to an increase of inequality in the short term; however it would even out in the long run. If the permanent component dominates the transitory, low earnings are a permanent rather than isolated experience.

Examples of factors contributing to the permanent component of earnings include changes in returns to education or skills, on-the-job training, or other factors that are relatively fixed from the point of view of an individual worker.²

In this paper, I decompose the annual variance of earnings into permanent and transitory components and study their evolution over time by fitting an error component model to observed second moments of earnings processes using Finnish data. My data are based on filed tax reports, so measurement

²It should be stressed that income volatility may or may not be equivalent to economic risk. As discussed in Blundell et al. (2008), earnings volatility does not necessarily translate into changes in welfare. Whether changes in earnings volatility have welfare implications depends on whether changes are anticipated and whether individuals are able to insure themselves against instability of earnings.

errors due to misreporting are arguably substantially smaller than in survey-based approaches.

The vast majority of existing studies on earnings dynamics concentrate solely on males, thereby making the implicit assumption that earnings inequality between male workers is a good measure for overall earnings inequality.³ The main contribution of this paper to the existing literature is that I present the decomposition of earnings separately for men and women. My approach echoes the observations of Korkeamäki & Kyyrä (2006), who, using Finnish data, found substantial differences in the educational background between men and women and also observed that occupations and firms tended to be segregated into those that were dominated by males and those by females. Consequently, a picture of earnings inequality solely based on males might be misleading. To get comparable figures for men and women, I limit my sample to working males and females and compare their earnings dynamics. Finally, my earnings data span the years 1988-2007, allowing me to study relatively recent developments in earnings dynamics.

My paper is heavily influenced by a series of articles that study earnings dynamics in other countries. Pioneering studies in this field include Gottschalk & Moffitt (1994), Moffitt & Gottschalk (2002), Baker (1997), and Haider (2001), all of which study earnings dynamics in the U.S. Following in their footsteps, Baker & Solon (2003) and Dickens (2000) present similar decompositions for Canada and the U.K., respectively. Due their access to a larger data set, they are able to fit more general models than the ones based on U.S. data. More recent papers using European registry based data fit variants of Baker & Solon (2003) and Dickens (2000). These include Gustavsson (2008), who studies Swedish panel data from 1960 to 1990, Ramos (2003) who studies British earnings data from the 1990s and Cappellari (2004), who studies Italian earnings data from the 1970s to 1990s. Even though the exact model specifications and time periods under consideration vary from country to country, the general finding is that there are significant differences between countries in terms of earnings dynamics. It is not clear whether the differences can be attributed to prevailing institutions or differences in the data. This creates a need to replicate the analysis using data from a new country. This paper is a scien-

³A notable exception is Ziliak et al. (2011), who report measures of permanent and transitory earnings inequality separately for men and women and for different educational groups, but do not limit their study to employed people.

tific replication study (using the terminology of Hamermesh 2007): it applies a rather well-established model to a new data.

To give a preview of the results, it transpires that increasing earnings inequality is driven by both the permanent and the transitory components; however their contribution is different for men and women. For men, permanent inequality predominates over transitory inequality. For women, they are of a similar magnitude. In addition, permanent earnings differences vary substantially between cohorts. There has also been a trend of increasing earnings instability for both sexes during the observation period.

This paper is structured as follows: Section 2.2 describes the data and the sample selection criteria applied. Section 2.3 introduces the model of earnings dynamics and outlines the estimation method. Section 2.4 provides the results and subsequent discussion. Section 2.5 contrasts the findings to previous studies. Section 2.6 offers conclusions.

2.2 Data and sample construction

The data consists of a panel of a one-third random sample of Finnish census. It covers the years 1988-2007.

The measure of earnings used in this paper is total annual labor earnings from employment. Earnings are calculated from individual tax files. To ensure comparability, all earnings are deflated to EUR 2007 using the Consumer Price Index. By definition, annual earnings are given by hourly wage multiplied by hours worked. Therefore, the observed earnings inequality reflects two dimensions of inequality, inequality in wages and inequality in hours worked. Consequently, the variance of annual earnings is higher than the variance of hourly wages unless the covariance of wages and hours worked is negative and large (Abowd & Card, 1989).

My measure of earnings inequality is variance of log annual labor earnings. Using variance of log earnings as a dependent variable is a standard approach in papers studying earnings dynamics because mathematical properties of variance are well established. In addition, correlation between the variance of log earnings and other widely used inequality measures is very high. Downside of this choice is that it is not measure-free. Thus, choice of currency unit and base year affects the measure of total earnings inequality. Nonetheless, the measure only affects the *level* of inequality, not the *changes*. Moreover, the

decomposition into permanent and transitory components is unaffected by the measure.

Registry data has some advantages over survey data. Since earnings information is collected by the authorities as a part of an administrative process, non-response and incorrect answers can be ruled out, which results in extremely reliable data on earnings.⁴ Attrition from the data can occur only by migration or death. In addition, definition of taxable labor earnings has remained unchanged for the period of observation.

Naturally, concentrating solely on labor earnings hides some of the income differences prevalent in the society. However, I have chosen this approach because supplementing the data by including capital income is not feasible due to limited available data. Moreover, including income transfers and paid taxes would introduce problems, because changes in tax laws and social security eligibility rules would severely limit the length of the panel. Another reason to prefer the measure of income chosen in this paper is that it is broadly equivalent to other papers published on the topic, thus facilitating international comparisons.

Another minor caveat in the data for the purposes of this paper is that earnings of over 200,000 Euros are top-coded due to statistical secrecy laws. This group is small (between .01 % and .05% of yearly observations), so their effect on the results is arguably small.

2.2.1 Sample selection criteria

The sample selection criteria were adapted from Haider (2001). They were chosen to ensure that the earnings dynamics of individuals in work are not confounded by people switching between work and non-work.

The target group in my sample is working males and females of prime age age between 26 and 60, who are observed for at least six years in total. I assume that by the age of 26, most people have completed their highest degrees.

I only include person-year observations if the main type of activity of a person is “working.” In other words, I exclude students, the unemployed, the retired, and other people outside the workforce. I limit my attention to people who are working because my interest is in the earnings dynamics of people

⁴Gottschalk & Huynh (2010) show that earnings inequality decompositions based on U.S. survey data most likely overstate total inequality due to non-classical measurement errors.

who are above the extensive margin. I also exclude working people with zero yearly earnings, as these observations are likely to have been misclassified.⁵

After applying the sample selection criteria, I am left with a “revolving unbalanced panel” (following the terminology of Haider, 2001). The panel is unbalanced because all the cohorts are not observed for all the years. The length of the panel varies between 6 and 20 years, depending on the cohort.

Since people are only included if they fulfill the selection criteria, they may enter and exit the panel. This feature makes the panel revolving. Applying a revolving, unbalanced panel mitigates problems related to compositional changes in the workforce due to the business cycle. If workers with unstable earnings only enter the workforce during an economic boom, they are only included in the data for those years, for which other selection criteria are fulfilled.

Since individuals with very volatile earnings are also more likely to permanently exit the panel, the approach chosen here introduces a potential selectivity bias to the estimates. Correcting for attrition is not feasible because the data lack instruments for selection. Still, the approach chosen here is less restrictive than analyses based on fully balanced panels. In addition, only including people with no breaks in their earnings histories would probably overstate the contribution of the permanent earnings component.

Previous papers studying the covariance structure of earnings concentrate solely on males. The underlying assumption behind this is that the labor force participation of men is more or less constant, whereas female labor force participation is jointly determined with family decisions (e.g. fertility), which may bias the results. Using a revolving balanced panel partially mitigates this problem, because only observations from working years are included. Therefore, transitions into and out of the workforce do not contribute to the empirical estimation. Nonetheless, it might be the case, that the working hours of females vary more than those of males, which may be reflected in female earnings variances. In addition, it is well established, both theoretically and empirically (see, e.g., Eckstein & Wolpin, 1989; Euwals et al., 2011), that a large negative earnings shock may promote female fertility decisions. Fertility decisions might then lower female wages due to their effect on work experi-

⁵The people are classified as working, if they have worked for over six months within a year. Therefore, even if there are some observations who are defined as “working”, they might have faced spells unemployment over the observation year.

ence of women. This mechanism introduces a specific kind of selectivity issue: women with high earnings shocks may voluntarily drop out of the workforce and concentrate on home production.⁶ Notwithstanding these caveats, the data should be representative of those women who are well attached to the labor force. Furthermore, the labor force participation rate of Finnish women is very high (Pissarides et al., 2003), which means that the endogenous participation of women is less of a problem than in some other countries.

A revolving balanced panel structure ensures that the measure of earnings inequality in this paper reflects the true earnings inequality of the population with good attachment to the labor market. Even though sample selection criteria somewhat differ from other studies, due to different structure of the data used, they are consistent within the observation period, thus enabling comparisons between years. Comparisons between countries, on the other hand, might be more questionable.

I categorize people into two year birth cohorts and follow each cohort through time. Studies based on a smaller data have been forced to pool all cohorts together due to small sample sizes. This naturally hides some of the heterogeneity of earnings dynamics between cohorts. The total size of the sample used in the analysis is given in Table 2.1.

2.2.2 Descriptive statistics of the covariance structure

In Figure 2.1, I plot the observed earnings variance for workers selected by the selection criteria given above. For both sexes, the variance decreases between the years 1988-1991 and thereafter rises until reaching its peak around 1994. After 1994 earnings inequality falls somewhat but remains high until the end of the sample period. The variances plotted in Figure 2.1 are somewhat higher than those observed in most other similar studies. This might be because I cannot discriminate between full-time and part-time workers. Moreover, in some studies based on income tax reports, earnings are censored from below, because income below the tax limit is not observed. This is not the case in this paper.

To grasp the essential features of earnings dynamics, it is useful to inspect the autocorrelation profiles of earnings by year and cohort. I have calculated

⁶It should be noted, that a similar mechanism might be present for male workers too: a large negative earnings shock may also induce men to drop out of the workforce.

| Cohort | Years observed | Age in initial year | Sample size (men) | Sample size (women) |
|-----------|----------------|---------------------|-------------------|---------------------|
| 1933-1934 | 1988-1994 | 55 | 2 882 | 3 673 |
| 1935-1936 | 1988-1996 | 53 | 5 169 | 6 579 |
| 1937-1938 | 1988-1998 | 51 | 7 383 | 8 954 |
| 1939-1940 | 1988-2000 | 49 | 8 595 | 9 987 |
| 1941-1942 | 1988-2002 | 47 | 10 398 | 11 736 |
| 1943-1944 | 1988-2004 | 45 | 11 593 | 12 877 |
| 1945-1946 | 1988-2006 | 43 | 16 817 | 18 481 |
| 1947-1948 | 1988-2007 | 41 | 18 760 | 19 801 |
| 1949-1950 | 1988-2007 | 39 | 18 026 | 19 311 |
| 1951-1952 | 1988-2007 | 37 | 17 735 | 18 784 |
| 1953-1954 | 1988-2007 | 35 | 17 643 | 18 982 |
| 1955-1956 | 1988-2007 | 33 | 18 377 | 18 926 |
| 1957-1958 | 1988-2007 | 31 | 17 610 | 17 769 |
| 1959-1960 | 1988-2007 | 29 | 18 060 | 17 562 |
| 1961-1962 | 1988-2007 | 27 | 18 447 | 16 932 |
| 1963-1964 | 1989-2007 | 26 | 18 720 | 16 700 |
| 1965-1966 | 1991-2007 | 26 | 17 945 | 15 930 |
| 1967-1968 | 1993-2007 | 26 | 17 688 | 15 357 |
| 1969-1970 | 1995-2007 | 26 | 16 057 | 13 476 |
| 1971-1972 | 1997-2007 | 26 | 15 095 | 12 209 |
| 1973-1974 | 1999-2007 | 26 | 14 248 | 11 343 |
| 1975-1976 | 2001-2007 | 26 | 13 482 | 9 548 |
| Total | | | 320 729 | 314 916 |

Table 2.1: Cohorts included in the analysis. Note: Age is defined by the older of the two birth cohorts.

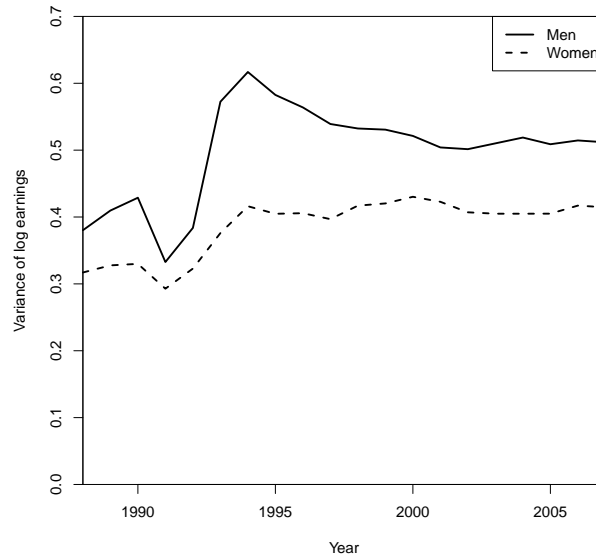


Figure 2.1: Yearly earnings inequality (measured by variance of log earnings of workers) of men (solid line) and women (dashed line)

yearly variance and autocovariances between years for people who are observed in both years. For cohorts who are observed for the full twenty years this adds up to 210 unique covariance elements ($21 \times 20/2$) and less for the other cohorts. In total, the unique elements of covariance matrices add up to 3,066 covariance elements.

Figure 2.2 presents the yearly variances and covariances between annual earnings for selected cohorts of men and women. Figure 2.2 shows that there are substantial differences in the variances and autocovariances of male and female earnings. This suggests that there are considerable differences in the earnings dynamics of men and women, making it reasonable to estimate separate models for the two sexes. In addition, a comparison of years reveals strong year effects. These are especially apparent during the recession of the early 1990s. The difference between variance and the first autocovariance is relatively large. In addition, autocovariances remain positive even at long lags, indicating that there are considerable permanent earnings differences. Finally, the variance and autocovariance values are larger for the oldest cohort, even at longer lags, which suggests the presence of cohort effects in the permanent component of earnings.

An alternative way to study cohort covariances is to keep the year fixed and plot covariances by age. This is done for three selected years in Figure 2.3. Comparing years reveals that income variances and covariances have risen over time for both men and for women, which indicates that earnings inequality has increased during the panel time and that at least part of this rise is due to a rise in permanent earnings differences. The variances are higher for young women than for young men, but as people grow older, the higher growth in variances of male earnings causes men to overtake women in terms of earnings inequality. The difference between the variance and autocovariances of earnings is at its largest for young women, indicating that high earnings inequality among young women is driven by transitory differences. For men, the difference between the variance and covariances remains almost constant, regardless of age.

To summarize, in addition to being able to disentangle permanent and transitory income differences, the preferred model for earnings inequality should reflect both cohort and year effects. The model should also allow variances of permanent and transitory components to change as people age.

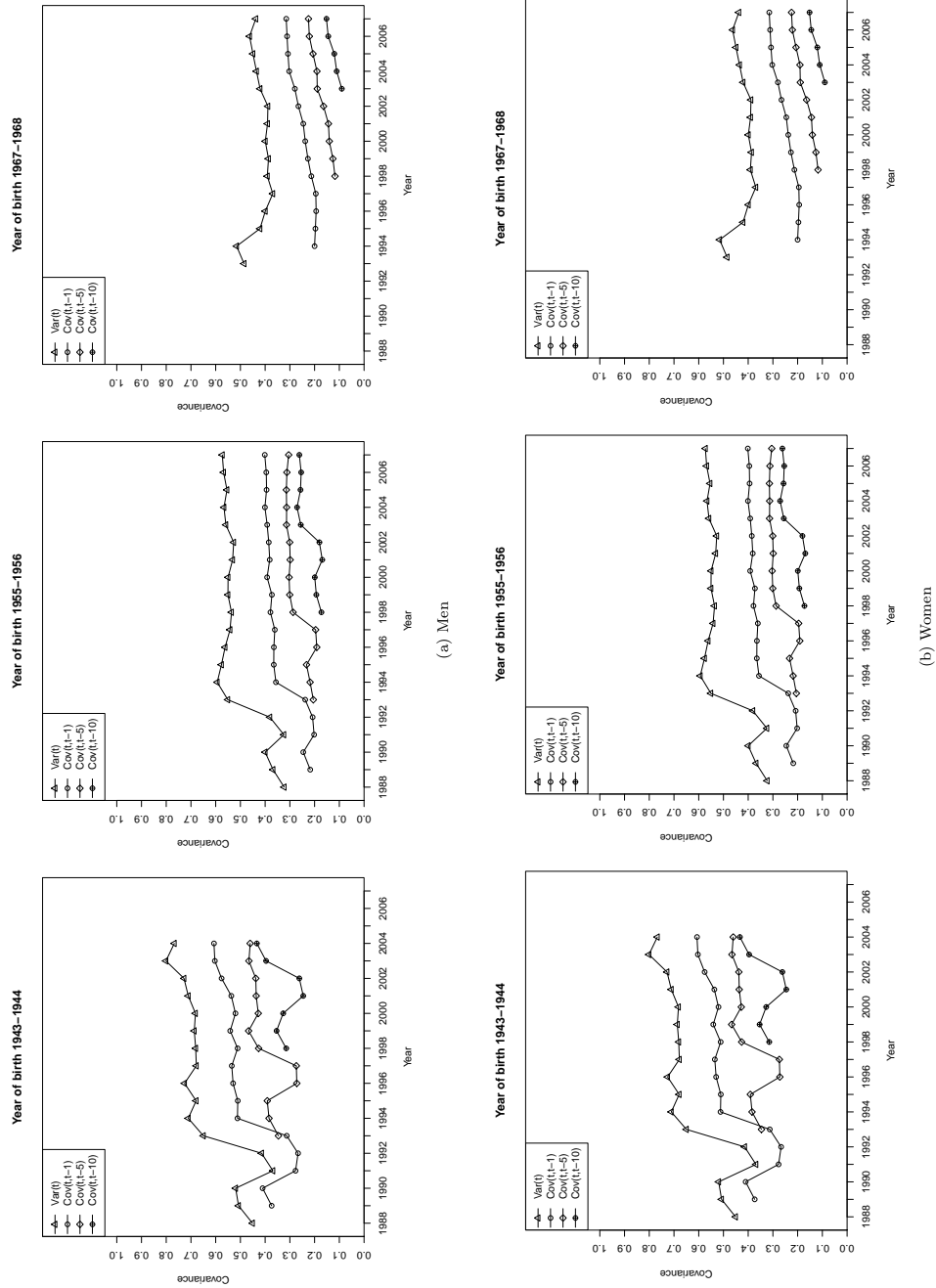


Figure 2.2: Autocovariances of yearly log earnings for selected cohorts

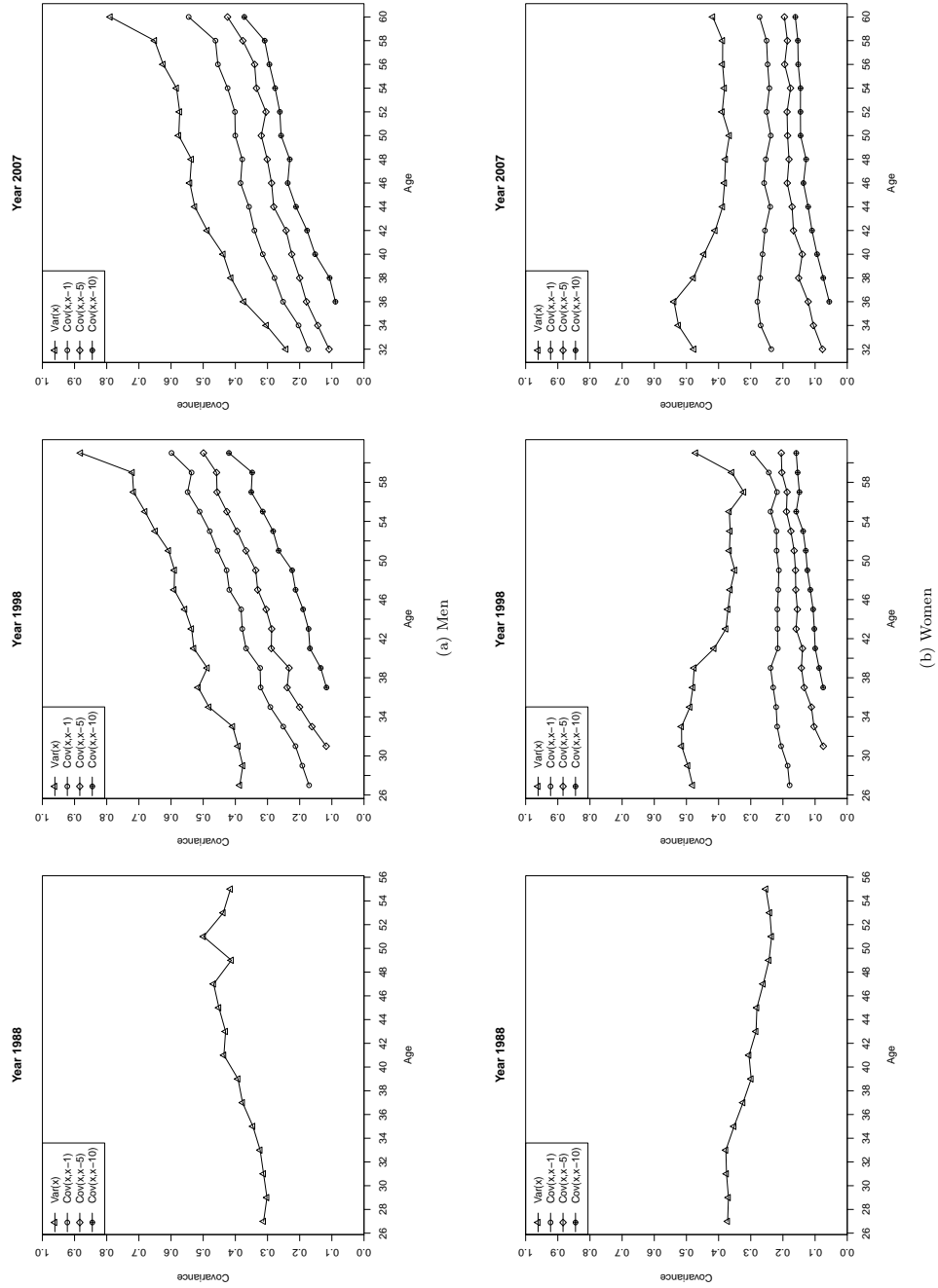


Figure 2.3: Autocovariances of yearly log earnings for selected years

2.3 Model and estimation

In this section, I introduce the econometric model and the estimation method. I estimate an error-components model with permanent and transitory components. The model allows individuals to permanently differ in their mean earnings as well as the earnings growth rate. The transitory component is modeled as an AR(1) process. As a result, even transitory shocks are allowed to exhibit persistence and can consequently take more than one year to flatten out.

2.3.1 Econometric model

Let Y_{ibt} denote log earnings in year t of person i born in year b . Individual earnings can be expressed as deviations from means, or

$$Y_{ibt} = \mu_{bt} + y_{ibt}.$$

Since my interest lies in the second moments of the distribution of Y_{ibt} , it suffices to write a model for de-meaned wages y_{ibt} . Expressing μ_{bt} as cohort-age means captures average year, age, and cohort effects in a more flexible fashion than using regression models with cohort-specific polynomials. The simplest possible model for y_{ibt} is

$$y_{ibt} = p_t \alpha_{ibt} + \lambda_t \varepsilon_{ibt} \quad (2.1)$$

where the two terms are assumed to be orthogonal to each other. Equation (2.1) can be seen as a Mincerian earnings equation of relative earnings, where α_{ibt} stands for the observed characteristics of individuals and ε_{ibt} is the error term. p_t and λ_t are year-specific factor loadings. Applying the variance operator to both sides yields

$$\text{Var}(y_{ibt}) = p_t^2 \sigma_\alpha^2 + \lambda_t^2 \sigma_\varepsilon^2. \quad (2.2)$$

Equation (2.2) gives the basic intuition of the decomposition. $p_t \sigma_\alpha^2$ denotes the variance of the permanent component of earnings, and $\lambda_t \sigma_\varepsilon^2$ denotes the variance of the transitory component. An increase in either component increases the dispersion of earnings, but an increase in $\lambda_t \sigma_\varepsilon^2$ also implies that churning within the earnings distribution increases.

Even though Equation (2.2) is intuitive, it may be too restrictive for two reasons. First, the variance of transitory shocks may exhibit age-related heteroskedasticity because workers at the start of their careers may have more unstable earnings.⁷ In addition, different cohorts may have different skills or other idiosyncratic features that affect the variability of their earnings. To incorporate these features, the following generalization of Equation (2.1) is used

$$y_{ibt} = q_b p_t u_{ibt} + \varepsilon_{ibt}, \quad (2.3)$$

where

$$u_{ibt} = \alpha_i + \beta_i x_t, \quad (2.4)$$

$$\varepsilon_{ibt} = \rho \varepsilon_{ibt-1} + \lambda_t \nu_{ibt}. \quad (2.5)$$

The terms α_i , β_i and ν_i are random variables first and second moments denoted as:

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \sim \left(\begin{bmatrix} \bar{\alpha} \\ \bar{\beta} \end{bmatrix}, \begin{bmatrix} \sigma_\alpha^2 & \sigma_{\alpha\beta} \\ & \sigma_\beta^2 \end{bmatrix} \right) \quad (2.6)$$

and

$$\nu_{ibt} \sim (\bar{\nu}, \gamma_0 + \gamma_1 x_t + \gamma_2 x_t^2). \quad (2.7)$$

x is defined as the potential experience of each cohort in year t , i.e., $x = t - b - 26$.

In Equation (2.4) u_{ibt} is a random growth term. It describes the permanent component of earnings. σ_α^2 reflects the variance of the earnings profiles of individuals at the age of 26, and the variance in σ_β^2 reflects the deviation of the individual-specific growth rate from the average growth rate of each cohort (the average growth rate is captured in μ_{bt}). p_t and q_c are year and cohort factor loadings, respectively.

The transitory component of earnings in (2.5) is given by a mean-reverting AR(1) process. λ_t are year-specific factor loadings on the innovation ν_{ibt} . This

⁷Meghir & Pistaferri (2004) report significant heteroskedasticity in earnings instability using U.S. data, albeit using a different model. Baker & Solon (2003) and Gustavsson (2008) reach similar conclusions using Canadian and Swedish data, respectively.

specification assumes that an earnings shock takes more than one year to flatten out and that earnings shocks accumulate over time. In addition, Equation (2.7) allows transitory variance to be a quadratic function of experience. The transitory and permanent components of earnings are assumed to be orthogonal to one another. To make identification possible, I have normalized p_{1988} and λ_{1989} and $q_{1951-1952}$ to 1.

Equations (2.3)–(2.7) generate non-stationarity to the variances of earnings processes through time-varying factor loadings for the permanent and the transitory components, p_t and λ_t . Another source of non-stationarity is the polynomial form of transitory shock variance. The intuition remains the same: a rise in p_t or q_c increases permanent income differences, whereas a rise in λ_t increases the shuffling of workers.

In line with the model specifications in Baker & Solon (2003) and Gustavsson (2008), polynomial form of $var(\nu_{ibt})$ recognizes that the earnings instability may vary between individuals because they are at different stages of their careers. The yearly factor loadings of the permanent and transitory components also give insights into the forces driving changes in income distribution.

The justification for the formulation in Equation (2.4) is both theoretical and empirical. For example, it has been successfully applied in Haider (2001), Ramos (2003), and Cappellari (2004), who demonstrate that in addition to allowing heterogeneity in mean earnings, the slope of earnings and the covariance of the two are important for capturing the dynamics of earnings. In most previous studies, the covariance term $\sigma_{\alpha\beta}$ is found to be negative. This is consistent with the on-the-job training hypothesis (see, e.g., Lillard & Weiss 1979; Hause 1980; and Baker 1997), which states that individuals may accept lower earnings at the beginning of their career, since they anticipate that their earnings will rise at a high enough rate and for a long enough time to compensate for low earnings at the beginning of their career. On the other hand, if $\sigma_{\alpha\beta}$ is found to be positive, it is consistent with the schooling-matching hypothesis, in which better skilled workers are endowed with more education, which raises their initial earnings and causes them to enjoy faster earnings growth as the quality of the match is revealed to their employers (Cappellari, 2004).

In addition to the specification in Equations (2.3)–(2.7), usually known as “random growth specification”, I have also experimented with other specifications, in particular, with the so called “random walk specification” (e.g., Gustavsson 2008), which is another widely used specification. This model is

given by $u_{ibt} = u_{ibt-1} + \xi_{it}$, where ξ_{it} is a white noise process. The main difference between the two formulations is that the random growth specification allows the correlation of the intercept and slope terms to be nonzero, whereas the random walk specification does not. In this sense, the random growth specification nests the random walk specification. Trials with the random growth specification always resulted in a statistically significant estimate for $\sigma_{\alpha\beta}$. I interpret this as a sign that the random walk model is inconsistent with the observed covariance structure of earnings.

Random walk and random growth specifications have different implications in terms of the age-derivative of cross-sectional variances. Under the random walk specification, the variance of earnings increases linearly with age, whereas under the random growth specification, the growth of permanent earnings inequality is either convex or concave, depending on the sign of $\sigma_{\alpha\beta}$ (Güvenen, 2009).⁸

2.3.2 Estimation

Direct estimation of a model based on equations (2.3)-(2.7) is inefficient, because it means estimating α_i and β_i for each individual with only a small number of observations. Since I am interested in the second moments of earnings distribution, I therefore estimate them directly. To accomplish this, I write down the variance of earnings in year t for cohort b implied by (2.3):

$$\begin{aligned} \text{Var}(y_{ibt}) &= q_b^2 p_t^2 [\sigma_\alpha^2 + x^2 \sigma_\beta^2 + 2x\sigma_{\alpha\beta}] + \\ &\quad \rho^2 \text{var}(\varepsilon_{ibt-1}) + \lambda_t^2 \text{var}(\nu_{ibt}). \end{aligned} \quad (2.8)$$

Respectively, a general covariance element between year t earnings and year $t-h$ ($h > 0$) earnings is given by⁹

$$\begin{aligned} \text{Cov}(y_{ibt}, y_{ibt-h}) &= q_b^2 p_t p_{t-h} [\sigma_\alpha^2 + x(x-h)\sigma_\beta^2 + (2x-h)\sigma_{\alpha\beta}] \\ &\quad + \rho^h \text{var}(\varepsilon_{ibt-h}). \end{aligned} \quad (2.9)$$

⁸Since random walk and random growth specifications do not necessarily rule each other out, some researchers (e.g. Baker & Solon, 2003 and Ramos, 2003) incorporate both into the same model. In my data, this specification either does not converge or results in negative variance estimates. Furthermore, the interpretation of these nested specifications is far from clear.

⁹Identification of earnings instability is made possible only by the off-diagonal elements of the covariance matrix. The underlying intuition is that a high correlation between earnings at t and earnings at $t-h$ implies a low instability of earnings.

The term $var(\varepsilon_{ibt})$ is calculated by backtracking the recursion in Equation (2.5) to the first sample year of each cohort. Since the earnings time series are relatively short, consequent covariances depend on the variance of the initial shock. This makes the standard time series analysis assumption of zero initial conditions problematic. I follow the suggestion of MaCurdy (1982; 2007) and treat the variances of initial shocks as extra parameters to be estimated. This parameter also takes into account transitory earnings differences accumulated before the start of the sample. These parameters are denoted by σ_b^2 .¹⁰

The unbalanced panel structure disentangles collinearity between experience and cohort effects from one another making it possible to identify all of them. If the were balanced panel, the difference between average experience levels between years t and $t + 1$ would be always identically one. With an unbalanced panel, the average experience level also grows between adjacent years, but its growth rate is not exactly one since some cohorts enter the panel and others exit from it.¹¹

Since the panel is revolving, an individual can only contribute to an element $(t, t - h)$ in the covariance matrix, if he or she is observed in years t and $t - h$. The sample covariances are thus calculated as the earnings covariance of people who are observed in both years. Consequently, people who have a higher attachment to the labor market contribute more to the empirical covariance matrices, which leads to a sample selection problem that cannot be completely overcome by unbalanced revolving panel construction. This is a common caveat in papers of this genre.

The estimation boils down to minimizing the distance between the cohort earnings covariances implied by the model and the empirical autocovariances calculated from the data. I stack each unique covariance matrix element into vector \mathbf{C} . The estimation is done by GMM, i.e., by minimizing a weighted distance between observed autocovariances \mathbf{C} and those implied by the model $\mathbf{F}(\theta)$, where θ is a vector of 87 parameters to be estimated. In practice, I

¹⁰Initial variance parameters have a different interpretation depending on whether earnings trajectories start from the age 26 or at a later age. For a cohort who has been 26 years of age before 1988, the initial variance is a measure of the transitory variance accumulated before 1988, whereas for a cohort who is observed for the first time after 1988, the initial variance is a measure of labor market conditions at the time of labor market entry.

¹¹Cohort, age, and year are naturally perfectly collinear for individual observations, but this does not hold for second moments of the population.

minimize the standard GMM criterion function

$$H = [\mathbf{C} - \mathbf{F}(\theta)]' \mathbf{W} [\mathbf{C} - \mathbf{F}(\theta)]. \quad (2.10)$$

Altonji & Segal (1996) demonstrate that using an asymptotically optimal GMM weighting matrix, i.e., choosing $\mathbf{W} = [\mathbf{F}(\theta)' \mathbf{F}(\theta)]^{-1}$, can lead to a very large finite-sample bias. This is due to $[\mathbf{F}(\theta)' \mathbf{F}(\theta)]$ being very close to singular. In line with the bulk of the earnings dynamics literature, I have chosen the identity matrix as the weighting matrix. This approach is called the Equally Weighted Minimum Distance estimation (Chamberlain, 1984). Using the identity matrix as the weighting matrix gives consistent but possibly inefficient estimates.

The asymptotic standard errors of vector θ are given by the standard GMM covariance matrix based on the fourth moments of the data. That is

$$\text{Var}(\theta) = (\mathbf{D}'\mathbf{D})^{-1} \mathbf{D}'\mathbf{\Omega}\mathbf{D} (\mathbf{D}'\mathbf{D})^{-1},$$

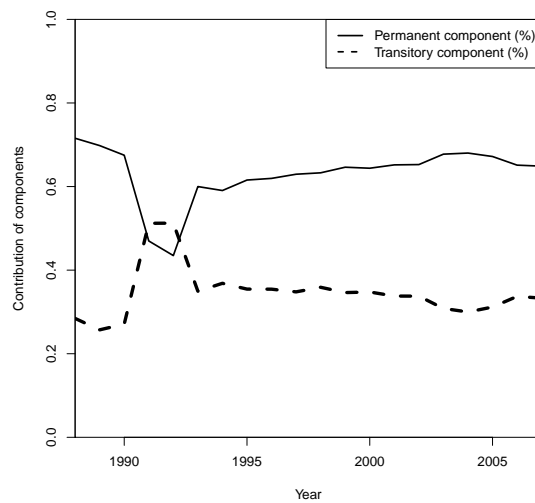
where $\mathbf{D} = \frac{\partial \mathbf{F}(\theta)}{\partial \theta'}$ and $\mathbf{\Omega} = [\mathbf{C} - \mathbf{F}(\theta)]' \mathbf{Q} [\mathbf{C} - \mathbf{F}(\theta)]$ are evaluated at the solution $\theta = \hat{\theta}$. \mathbf{Q} is a block diagonal matrix of ones. Including \mathbf{Q} in the matrix product effectively sets the covariances between cohorts at zero.

2.4 Estimation results

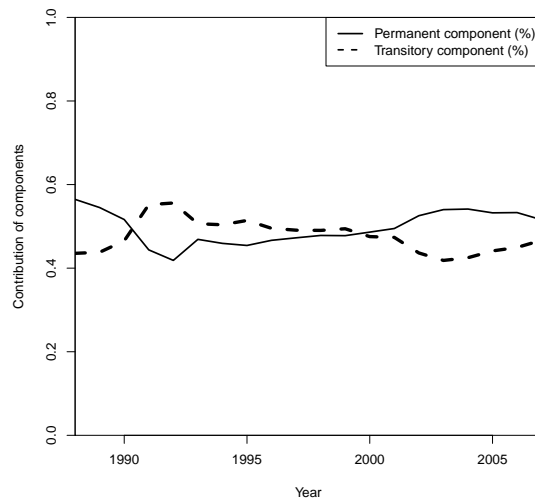
2.4.1 Parameter estimates

Figure 2.4 decomposes total earnings inequality into its permanent and transitory components. The decomposition is based on equation (2.8). The term $p_t^2 [\sigma_\alpha^2 + x^2 \sigma_\beta^2 + 2x\sigma_{\alpha\beta}]$ accounts for the permanent component of earnings and term $\rho^2 \text{var}(\varepsilon_{ibt-1}) + \lambda_t^2 \text{var}(\nu_{ibt})$ accounts for the transitory component.

The contribution of permanent earnings inequality to total inequality is larger for men than for women in almost all years. This implies that permanent inequality among men is larger than among women. The contribution of the permanent component has remained roughly similar throughout the sample, with the exception of the recession years 1991 and 1992. Even though the magnitude of the two components differ between sexes, the dynamics of the two components were roughly similar for both sexes for the entire sample period.



(a) Men



(b) Women

Figure 2.4: Decomposition of the variance of log earnings among men and women measured in percentages. Predicted variance is calculated as the sum of the persistent and transitory components

| | Men Parameter | S.E. | Women Parameter | S.E. |
|-----------------|------------------|---------------|--------------------|---------------|
| p_{1988} | 1 | | 1 | |
| p_{1989} | 1.017 | 0.010 | 0.983 | 0.011 |
| p_{1990} | 1.014 | 0.009 | 0.944 | 0.010 |
| p_{1991} | 0.737 | 0.019 | 0.811 | 0.009 |
| p_{1992} | 0.754 | 0.019 | 0.813 | 0.008 |
| p_{1993} | 1.071 | 0.016 | 0.913 | 0.012 |
| p_{1994} | 1.102 | 0.016 | 0.937 | 0.009 |
| p_{1995} | 1.094 | 0.018 | 0.907 | 0.012 |
| p_{1996} | 1.079 | 0.016 | 0.908 | 0.016 |
| p_{1997} | 1.063 | 0.014 | 0.892 | 0.015 |
| p_{1998} | 1.058 | 0.017 | 0.907 | 0.016 |
| p_{1999} | 1.067 | 0.020 | 0.898 | 0.016 |
| p_{2000} | 1.054 | 0.016 | 0.904 | 0.013 |
| p_{2001} | 1.043 | 0.014 | 0.894 | 0.015 |
| p_{2002} | 1.043 | 0.015 | 0.893 | 0.015 |
| p_{2003} | 1.063 | 0.014 | 0.889 | 0.012 |
| p_{2004} | 1.067 | 0.013 | 0.876 | 0.011 |
| p_{2005} | 1.044 | 0.013 | 0.855 | 0.012 |
| p_{2006} | 1.028 | 0.013 | 0.854 | 0.013 |
| p_{2007} | 1.017 | 0.015 | 0.825 | 0.012 |
| $q_{1933-1934}$ | 0.977 | 0.016 | 0.777 | 0.010 |
| $q_{1935-1936}$ | 1.054 | 0.012 | 0.846 | 0.007 |
| $q_{1937-1938}$ | 1.076 | 0.009 | 0.847 | 0.005 |
| $q_{1939-1940}$ | 1.005 | 0.007 | 0.876 | 0.004 |
| $q_{1941-1942}$ | 1.049 | 0.005 | 0.904 | 0.003 |
| $q_{1943-1944}$ | 1.047 | 0.004 | 0.940 | 0.003 |
| $q_{1945-1946}$ | 1.033 | 0.003 | 0.938 | 0.002 |
| $q_{1947-1948}$ | 1.034 | 0.002 | 0.958 | 0.001 |
| $q_{1949-1950}$ | 1.004 | 0.001 | 0.971 | 0.001 |
| $q_{1951-1952}$ | 1 | | 1 | |
| $q_{1953-1954}$ | 1.000 | 0.001 | 1.014 | 0.001 |
| $q_{1955-1956}$ | 1.004 | 0.002 | 1.059 | 0.002 |
| $q_{1957-1958}$ | 1.026 | 0.004 | 1.097 | 0.003 |
| $q_{1959-1960}$ | 1.010 | 0.005 | 1.148 | 0.005 |
| $q_{1961-1962}$ | 1.037 | 0.007 | 1.187 | 0.007 |
| $q_{1963-1964}$ | 1.018 | 0.009 | 1.192 | 0.010 |
| $q_{1965-1966}$ | 0.992 | 0.011 | 1.217 | 0.012 |
| $q_{1967-1968}$ | 0.952 | 0.013 | 1.223 | 0.015 |
| $q_{1969-1970}$ | 0.922 | 0.015 | 1.267 | 0.018 |
| $q_{1971-1972}$ | 0.907 | 0.017 | 1.260 | 0.023 |
| $q_{1973-1974}$ | 0.863 | 0.020 | 1.294 | 0.031 |
| $q_{1975-1976}$ | 0.774 | 0.026 | 1.129 | 0.050 |
| σ_a^2 | 0.156 | 0.003 | 0.093 | 0.002 |
| σ_b^2 | $1.5 * 10^{-5}$ | $8 * 10^{-6}$ | $2.9 * 10^{-5}$ | $6 * 10^{-6}$ |
| σ_{ab} | 0.004 | $2 * 10^{-4}$ | 0.004 | $1 * 10^{-4}$ |

Table 2.2: Estimated parameters of permanent component of earnings.

| | Men | | Women | |
|------------------------|----------------|-----------------|----------------|---------------|
| | Parameter | S.E. | Parameter | S.E. |
| λ_{1988} | (unrestricted) | | (unrestricted) | |
| λ_{1989} | 1 | | 1 | |
| λ_{1990} | 1.057 | 0.018 | 1.043 | 0.019 |
| λ_{1991} | 1.279 | 0.067 | 1.086 | 0.024 |
| λ_{1992} | 1.380 | 0.066 | 1.156 | 0.024 |
| λ_{1993} | 1.384 | 0.050 | 1.207 | 0.028 |
| λ_{1994} | 1.487 | 0.060 | 1.273 | 0.031 |
| λ_{1995} | 1.413 | 0.057 | 1.276 | 0.032 |
| λ_{1996} | 1.395 | 0.063 | 1.254 | 0.036 |
| λ_{1997} | 1.349 | 0.065 | 1.244 | 0.037 |
| λ_{1998} | 1.366 | 0.079 | 1.277 | 0.039 |
| λ_{1999} | 1.335 | 0.068 | 1.297 | 0.043 |
| λ_{2000} | 1.331 | 0.075 | 1.290 | 0.047 |
| λ_{2001} | 1.290 | 0.072 | 1.287 | 0.047 |
| λ_{2002} | 1.288 | 0.073 | 1.214 | 0.051 |
| λ_{2003} | 1.243 | 0.071 | 1.203 | 0.062 |
| λ_{2004} | 1.239 | 0.076 | 1.230 | 0.057 |
| λ_{2005} | 1.253 | 0.071 | 1.271 | 0.054 |
| λ_{2006} | 1.312 | 0.080 | 1.319 | 0.050 |
| λ_{2007} | 1.302 | 0.073 | 1.358 | 0.045 |
| $\sigma^2_{1933-1934}$ | 0.025 | 0.009 | 0.058 | 0.005 |
| $\sigma^2_{1935-1936}$ | 0.003 | 0.009 | 0.023 | 0.004 |
| $\sigma^2_{1937-1938}$ | 0.067 | 0.009 | 0.029 | 0.004 |
| $\sigma^2_{1939-1940}$ | 0.054 | 0.007 | 0.035 | 0.004 |
| $\sigma^2_{1941-1942}$ | 0.097 | 0.008 | 0.053 | 0.004 |
| $\sigma^2_{1943-1944}$ | 0.101 | 0.007 | 0.071 | 0.004 |
| $\sigma^2_{1945-1946}$ | 0.109 | 0.007 | 0.088 | 0.004 |
| $\sigma^2_{1947-1948}$ | 0.132 | 0.006 | 0.117 | 0.004 |
| $\sigma^2_{1949-1950}$ | 0.123 | 0.006 | 0.120 | 0.003 |
| $\sigma^2_{1951-1952}$ | 0.128 | 0.005 | 0.150 | 0.003 |
| $\sigma^2_{1953-1954}$ | 0.113 | 0.005 | 0.188 | 0.003 |
| $\sigma^2_{1955-1956}$ | 0.106 | 0.004 | 0.216 | 0.003 |
| $\sigma^2_{1957-1958}$ | 0.103 | 0.004 | 0.220 | 0.003 |
| $\sigma^2_{1959-1960}$ | 0.117 | 0.004 | 0.218 | 0.003 |
| $\sigma^2_{1961-1962}$ | 0.135 | 0.003 | 0.230 | 0.002 |
| $\sigma^2_{1963-1964}$ | 0.141 | 0.004 | 0.227 | 0.004 |
| $\sigma^2_{1965-1966}$ | 0.210 | 0.004 | 0.254 | 0.002 |
| $\sigma^2_{1967-1968}$ | 0.323 | 0.005 | 0.357 | 0.002 |
| $\sigma^2_{1969-1970}$ | 0.281 | 0.003 | 0.361 | 0.002 |
| $\sigma^2_{1971-1972}$ | 0.246 | 0.003 | 0.318 | 0.003 |
| $\sigma^2_{1973-1974}$ | 0.255 | 0.004 | 0.362 | 0.004 |
| $\sigma^2_{1975-1976}$ | 0.205 | 0.005 | 0.318 | 0.007 |
| ρ | 0.223 | 0.012 | 0.226 | 0.009 |
| γ_0 | 0.112 | 0.013 | 0.249 | 0.015 |
| γ_1 | -0.001 | 0.001 | -0.011 | 0.001 |
| γ_2 | $9 * 10^{-6}$ | $2.7 * 10^{-5}$ | $2 * 10^{-4}$ | $3 * 10^{-5}$ |

Table 2.3: Estimated parameters of transitory variance of earnings.

The transitory components of the earnings inequality of men and women are highly correlated, although the transitory inequality is higher for women. Tables 2.2 and 2.3 present the estimates of the parameters of the permanent and transitory components. I will discuss both parameters in turn.

An initial glance at Tables 2.2 and 2.3 shows that most parameter estimates have very small standard errors. That is, they are accurately estimated, in spite of the model being flexibly parameterized and including year, cohort, and experience effects. Table 2.2 reports the parameters of permanent earnings differences. The level term σ_α^2 is statistically significantly larger for men than it is for women. The slope term σ_β^2 and the correlation term $\sigma_{\alpha\beta}$ are of similar magnitude for both sexes. Moreover, the estimated correlation between the intercept and slope terms is positive. This means that people who have higher initial earnings also have larger earnings growth. As a result, the permanent part of earnings distribution becomes increasingly unequal over the life cycle.

For men, yearly loadings on the permanent earnings component are almost constant, except for the two deepest recession years. For women, there is a downward trend in yearly loadings, indicating that permanent earnings differences have decreased during the end of the 1990s and early 2000s. Changes in the permanent component yearly loading can be interpreted as the prices of the fixed skills of individuals, keeping cohort effects constant.

The deep Finnish recession experienced by Finland in the early 1990s is visible as a drop in the permanent earnings inequality component.¹² The explanation for this drop is that people with lowest wages dropped out of the workforce, which had the effect of decreasing earnings inequality. However, the effect of the recession is much less clear in the time series of transitory shocks.

Next, I will turn to estimates for cohort loadings on the permanent component q_c . The most intuitive interpretation for the cohort loadings of permanent component is that they are a measure of the dispersion of the skills within a cohort. An alternative interpretation for q_c is that they reflect very persistent shocks that affect cohorts differently even if the skill dispersion of cohorts does not change. An example of such shocks is the long-term wage scarring effect of graduating in a recession (see, e.g., Kwon et al. 2010, and Oreopoulos & von

¹²Finland experienced the deepest economic recession experienced in any industrialized country since the 1930s. For details, see, e.g., Gorodnichenko et al. (2012) and Honkapohja & Koskela (1999).

Wachter 2008).

Coinciding with the decrease in yearly factor loadings for women is the increase in cohort loadings for the permanent component of earnings. This implies that earnings inequality for all women has decreased since the 1990s, but at the same time, younger cohorts are more unequal than older cohorts. In other words, as younger cohorts have become more skilled, within cohort inequality has increased but at the same time the inequality between cohorts has decreased. For men, however, the inequality time-trend is exactly the opposite: the younger cohorts are more equal than the older ones.

Finally, I will turn to the estimates for the transitory component reported in the bottom four rows of Table 2.3. The estimate for the AR coefficient is 0.22 for men and women. The age profile of variance of the transitory shocks, visualized in Figure 2.5, is strikingly different between men and women. For men, γ_1 and γ_2 do not differ from zero at conventional risk levels, which implies that there is no age-related heteroskedasticity in the variance of transitory shocks. For women, on the other hand, the variance of transitory shocks is decreasing and convex. For women under 30, transitory shock variance is over double that of men. Furthermore, regardless of the cohort, initial earnings shocks are considerably higher for women than for men. This observation is roughly consistent with Lundberg & Rose (2000), who find that motherhood decreases the labor supply of married women who are attached to the labor market but not their wages.

Yearly loadings on the transitory component of earnings λ_t also exhibit different trends for men and women.¹³ For men, they peak in 1994, whereafter, they decline somewhat but still remain above one until 2007. For women, there is an almost constant rise from 1988 to 2007.

Adding cohort loadings to the transitory component always resulted in convergence problems. This suggests that combining cohort loadings of the transitory component with the cohort specific initial variances (σ_b^2) over-parameterize the model. Therefore, earnings instability seems to be symmetric for all cohorts when initial conditions have been accounted for. Earnings instability seems to be more related to labor market conditions prevailing in society than

¹³To ensure that initial variance parameters are only identified by the initial variance in cohort's first sample year, λ_{1988} is left unrestricted and λ_{1989} is normalized to 1. Without this restriction, yearly loadings on the transitory component and the initial variances could not be jointly identified.

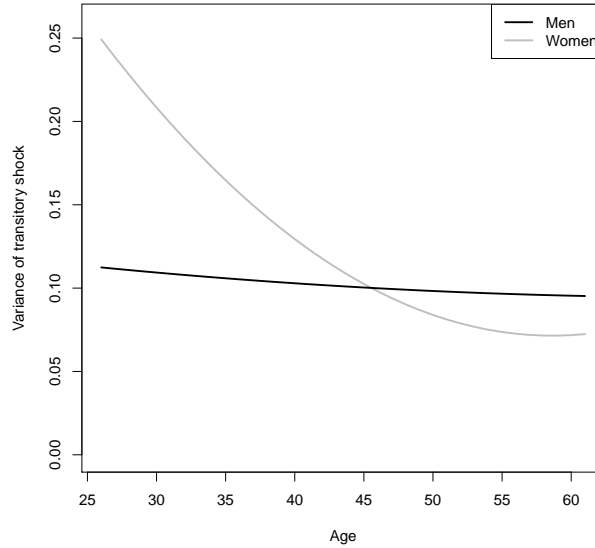


Figure 2.5: Variance of the transitory shocks of men and women as a function of age.

to differences in the human capital within cohorts. Nonetheless, for both sexes, the contribution of rising earnings instability to inequality is substantial.

2.4.2 Decomposition analysis: cohorts and years

The parameter estimates only give a partial description of the evolution of earnings dynamics. As discussed in the previous subsection, there is substantial variation between cohorts and years. To get further insight into these differences, this subsection introduces counterfactual analyses, which are obtained by eliminating sets of parameters in turn.

Figure 2.6 plots the contributions of the cohort and the year effects on permanent inequality. For men, setting the year effects to 1 eliminates most of the permanent differences. This is consistent with the notion that permanent earnings differences of males are driven by the changes in returns to skill rather than differences in the skill composition of cohorts. However, the same explanation does not apply for females, as eliminating the year effects in permanent component actually increases female earnings inequality. This suggests that

permanent female inequality is driven by within cohort inequality rather than year-to-year changes.

Turning to transitory earnings differences, plotted in Figure 2.7, we see similar patterns for men and women. Eliminating the year loadings flattens most of the transitory shocks. This unequivocally suggests that earnings have become more unstable for both sexes. The slight downward trend in the transitory inequality of females is explained by the age-gradient of the transitory shock variance: older people face smaller transitory shocks.

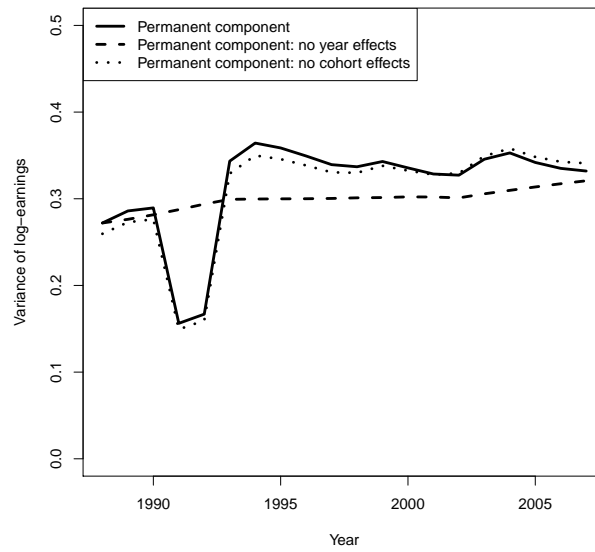
The underlying assumption in the preceding discussion is that the model is correctly specified and all of the parameters are strongly identified. The following section discusses the evidence in favor of strong identification.

wh

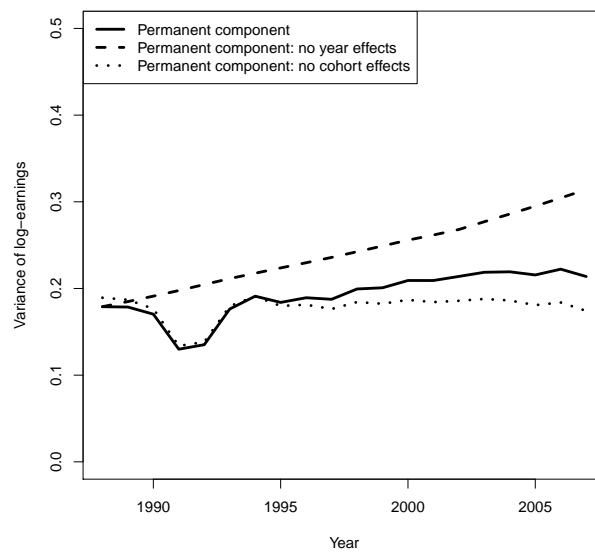
2.4.3 Sensitivity of results to model specification

Generally, weak identification can arise if the moment condition is small, but not zero, at a range of values differing from the true parameter value θ_0 . Stock & Wright (2000) show that the asymptotic theory devised for identified models is invalid for weakly identified models. As a result, the parameter estimates of weakly identified models are inconsistent, and the calculated covariance matrix does not converge to the true covariance matrix, which results in invalid estimates for standard errors. Furthermore, even if most parameters are strongly identified, their asymptotic standard errors might be invalid in the presence of some weakly identified parameters. In the context of this paper, weak identification may arise if ρ is close to 1. If $\rho \approx 1$, the transitory component is "very close to being permanent". This causes problems in identification, since both the transitory and permanent components reflect relatively permanent earnings inequality making it difficult to distinguish them from one another, especially if the panel length is short.

Doris et al. (2012) gives Monte Carlo evidence on the ranges of parameter values that lead to biased estimates. According to Tables 2a and 3 in their paper, a model estimated using eight panel years of observations and $\rho = .8$ is sufficient to give unbiased results. Since my panel length is well over that for most cohorts (median panel length in my data is 17 years) and my estimates of ρ are well below .8, I am confident about the strong identification of the models estimated. In addition, linear time trends in any factor loading might

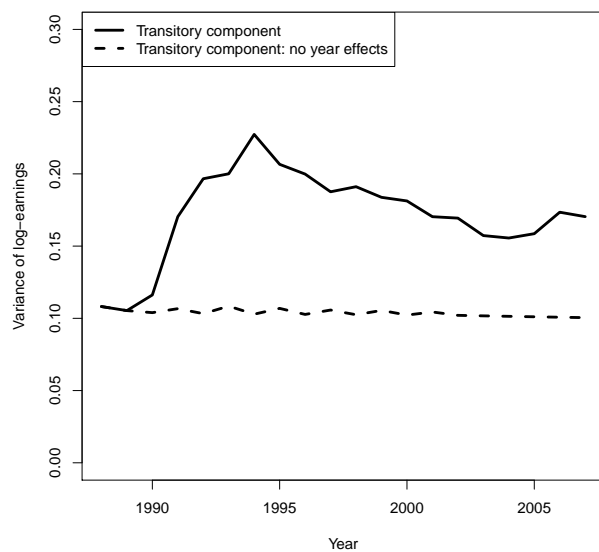


(a) Men

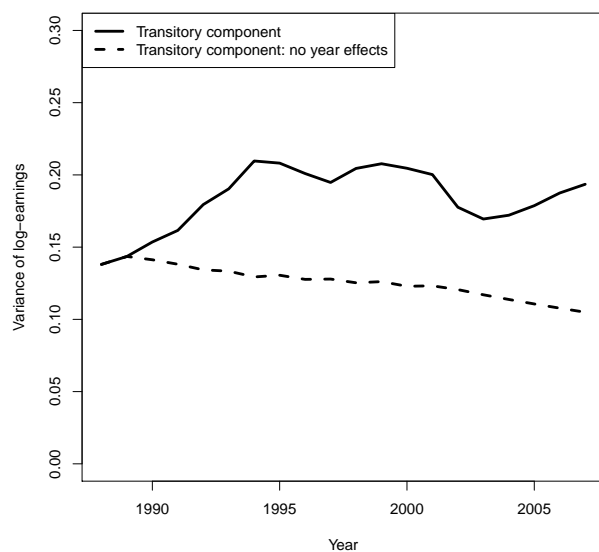


(b) Women

Figure 2.6: The effects of eliminating year and cohort loadings on permanent earnings inequality for men and women.



(a) Men



(b) Women

Figure 2.7: The effects of eliminating year loadings on transitory earnings inequality for men and women.

also cause problems in identification. Such trends are not present in my data.

I have not applied Newey's (1985) specification test to assess the goodness of fit, because a general finding in the earnings dynamics literature is that the null hypothesis of a correctly specified model is almost always rejected. According to Baker & Solon (2003), these tests have inflated sizes when the amount of overidentifying restrictions is as large as in this case (3,066 moment conditions used to identify 87 parameters).

Another possible caveat, according to the warnings given in Baker & Solon (2003) and Shin & Solon (2011), is that an arbitrary change in a parametric model may lead to different conclusions. I have experimented with alternative specifications (given in Table 2.4) and do not find cause for concern. First, as is evident from the difference in the mean squared errors (MSE's) between the random growth and random walk models and the statistically significant estimate of $\sigma_{\alpha\beta}$, the data clearly reject the simpler random walk specification in favor of the random growth specification.

Second, the model with an ARMA(1,1) specification for the transitory component gives similar results to the AR(1) specification. The main difference in these two specifications is that the inclusion of the MA(1) parameter reduces the absolute value of the persistence parameter ρ . This difference is statistically significant for women but not for men. Inclusion of the MA(1) parameter does not have a jointly statistically significant impact for other parameters than ρ .

| | Random walk + AR(1) Parameter | S.E. | Random growth + AR(1) Parameter | S.E. | Random growth + ARMA(1,1) Parameter | S.E. |
|------------------------|----------------------------------|-----------------|------------------------------------|-----------------|--|-----------------|
| Men | | | | | | |
| Permanent component | | | | | | |
| σ_α | 0.209 | 0.008 | 0.156 | 0.003 | 0.157 | 0.003 |
| σ_β | $3.7 * 10^{-5}$ | $1.5 * 10^{-5}$ | $1.5 * 10^{-5}$ | $8 * 10^{-6}$ | $1.4 * 10^{-5}$ | $8 * 10^{-6}$ |
| $\sigma_{\alpha\beta}$ | (restricted to 0) | | 0.004 | $2 * 10^{-4}$ | 0.004 | 0.000 |
| Transitory component | | | | | | |
| ρ | 0.87 | 0.016 | 0.223 | 0.012 | 0.258 | 0.042 |
| δ | (restricted to 0) | | (restricted to 0) | | -0.032 | 0.041 |
| γ_0 | 0.084 | 0.007 | 0.112 | 0.013 | 0.112 | 0.013 |
| γ_1 | 0.003 | 0.001 | -0.001 | 0.001 | -0.001 | 0.001 |
| γ_2 | $-9.3 * 10^{-5}$ | $2.3 * 10^{-5}$ | $9 * 10^{-6}$ | $2.7 * 10^{-5}$ | $9 * 10^{-6}$ | $2.7 * 10^{-5}$ |
| Mean Square Error | 1.81 | | 1.29 | | 1.29 | |
| Women | | | | | | |
| Permanent component | | | | | | |
| σ_α | 0.110 | 0.006 | 0.093 | 0.002 | 0.092 | 0.002 |
| σ_β | $7 * 10^{-6}$ | $1.1 * 10^{-5}$ | $8 * 10^{-6}$ | $2.9 * 10^{-5}$ | $3.1 * 10^{-5}$ | $7 * 10^{-6}$ |
| $\sigma_{\alpha\beta}$ | (restricted to 0) | | 0.004 | $1 * 10^{-4}$ | 0.004 | $1 * 10^{-4}$ |
| Transitory component | | | | | | |
| ρ | 0.634 | 0.08 | 0.226 | 0.009 | 0.154 | 0.019 |
| δ | (restricted to 0) | | (restricted to 0) | | 0.069 | 0.026 |
| γ_0 | 0.228 | 0.011 | 0.249 | 0.015 | 0.251 | 0.014 |
| γ_1 | -0.007 | 0.001 | -0.011 | 0.001 | -0.011 | 0.001 |
| γ_2 | $5.5 * 10^{-5}$ | $3.2 * 10^{-5}$ | $2 * 10^{-4}$ | $3 * 10^{-5}$ | $2 * 10^{-4}$ | $3 * 10^{-5}$ |
| MSE | 1.42 | | 0.69 | | 0.68 | |

Table 2.4: Comparison of model specifications.

2.5 Comparison to other studies

To better grasp which of the differences between this paper and papers using data from other countries are due to differences in econometric modeling choices or data and which are due to prevailing institutional differences, this section contrasts the central findings of this with previous studies. Two findings in this paper are different from most previous papers: the sign of the correlation between earnings growth and intercept components, $\sigma_{\alpha\beta}$, and the autocorrelation coefficient of the transitory earnings component ρ .

My estimate for $\sigma_{\alpha\beta}$ is positive for both sexes, which implies that the distribution of earnings widens as people age. Cappellari (2004) reports a similar finding for Italy, but other studies I am aware of (Haider, 2001; Baker & Solon, 2003; Baker, 1997; Gustavsson, 2008; Ramos, 2003) report a negative parameter estimate. It is difficult to judge whether these differences are more due to data construction or institutional differences. Nonetheless, it should be noted that the studies that find $\sigma_{\alpha\beta} < 0$ use various earnings measures as well as data sources.

Since I do not observe hours worked by an individual, I am not able to discriminate between full-time and part-time workers. This inevitably affects some of the results. Consequently, my estimates for the contribution of the transitory component to total inequality are much larger than those obtained in studies concentrating only on full time workers (these include Baker & Solon, 2003; Haider, 2001; Gustavsson, 2008). Moreover, the persistence of transitory shocks is found to be considerably lower. Baker & Solon (2003), Dickens (2000), and Haider (2001) report estimated autocorrelation values in the range of 0.6 and 0.95, however, they concentrate on full-time working males. In contrast, Ramos (2003) does not discriminate between full-time and part-time workers. He finds that the transitory component may account for up to 80 percent of yearly earnings variance. Ramos also finds $\hat{\rho}$ estimates in the range of 0.29 and 0.41, which are considerably closer to my estimates.

Another partial explanation to the low estimated persistence of transitory shocks is that, generally speaking, random walk specification results in higher persistence compared to random growth specifications. Indeed, Guvenen (2009) shows analytically that if a random growth model is misspecified as a random walk model, the persistence parameter ρ will be biased upwards.

Making comparisons between other countries is also somewhat suspect,

because separating prevailing differences in labor market conditions from differences in the data is far from straightforward. The most comparable study to the current one in terms of data is Ramos (2003), who studies male earnings inequality in the U.K. between 1991 and 1999. Most notable difference between the results in Ramos (2003) and those in this study are that Ramos finds that older workers face very unstable earnings compared to younger workers. For example, according to his estimates, the transitory component constitutes over 80 per cent of the total income variance for a cohort over 50 years old at the end of the observation period. This is considerably higher than my findings; and it is most likely attributable to institutional differences (e.g., a higher proportion of part-time workers over 50 in Great Britain compared to Finland).

2.6 Summary and conclusions

Previous research has shown that earnings inequality has risen in Finland during the last two decades. This paper decomposes the yearly Finnish log earnings variance of the working population into its permanent and transitory components. The analysis is done separately for men and women. The econometric analysis is based on the second moments of log-earnings distribution using the Equally Weighted Minimum Distance method of Chamberlain (1984).

I find that the increase in earnings inequality among men and women is driven by both the permanent and transitory components, but the contributions of these components are of different magnitude. The permanent component of earnings inequality is larger for men than for women. As a corollary, men enjoy more stable income paths but with larger permanent earnings differences. Women, on the other hand, experience more unstable earnings processes but have smaller permanent differences in earnings.

The age-derivative of the permanent earnings inequality of men and women is similar, indicating that the relative differences in permanent earnings stay similar throughout the careers of men and women. The correlation between initial earnings inequality and the growth in earnings inequality is found to be positive for both sexes, implying a divergence of earnings profiles and increasing permanent earnings differences toward the end of individuals' working career. Compared to findings, in other countries the persistence of transitory earnings shocks is found to be relatively small. Moreover, the contribution

of transitory shocks to inequality has risen considerably for both sexes. This strongly suggests that earnings have become more unstable during the last 20 years.

Finding ultimate causes for the changes in persistent and transitory inequality is beyond the scope of this paper, but some tentative explanations can be offered. For both sexes, we see that year loadings on the permanent inequality drive a lot of the earnings differences. This might be due to yearly changes in labor demand. On the other hand, the larger cohort effects of younger cohorts on permanent female earnings inequality suggest that younger working women face higher permanent earnings inequality than older women. It seems plausible that this is due to the high labor force participation of young women rather than changing returns to skill, as there is no such trend for cohorts of men.

Finally, the lessons of this paper suggest that researchers applying estimates obtained from these types of models in their work may inadvertently miss potentially important aspects of the earnings dynamics prevalent in society if they only concentrate on males.

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Chapter 3

Uncertainty and Heterogeneity in Returns to Education: Evidence from Finland

Abstract

This paper studies the causal effect of education on income uncertainty using a broad measure of income which encompasses unemployment risk. To accomplish this, the variance of residuals from a Mincer-type income regression is decomposed into unobserved heterogeneity (known to the individuals when making their educational choices) and uncertainty (unknown to the individual). The estimation is done using Finnish registry data. The effect of having secondary or lower tertiary level education decreases income uncertainty. University level education is found to have a small positive marginal effect on income uncertainty. The effect of education on income uncertainty is roughly similar for men when compared to women, but income uncertainty is larger for men than for women regardless of education. Contrary to some results from the U.S., the role of unobserved heterogeneity is found to be very small.

3.1 Introduction

Return to education is perhaps the most widely studied causal relationship in contemporary economic literature. A central message from this literature is that measuring monetary return to education is complicated by endogenous selection. Endogenous selection arises simply from the fact that people who choose different levels of education levels are likely to differ from one another in some dimensions unobservable to the researcher. Neglecting this unobserved heterogeneity may potentially bias into return estimates. Monetary uncertainty in return to education has received much smaller empirical attention. The return to education varies between individuals and materializes possibly only several years after the choice of education has been made, which imply that educational investment has an inherent uncertainty to it. Analogously to estimating mean returns to education, endogenous selection also complicates the estimation of uncertainty in monetary returns to education.

The measure of earnings uncertainty used throughout this paper is the variance of yearly income. A direct comparison of income variances between university and high school educated people might give an incorrect picture of the effect of education on income variance, because we cannot observe counterfactual income streams of the same people with different education levels. Consequently, the observed variance of income may not be a good measure of uncertainty, because it is comprised of two distinct components: unobserved heterogeneity and uncertainty. The intuition for this dichotomy follows from private information: earnings uncertainty, or risk, is the part of the earnings variance, which is not foreseeable by the decision-maker.

Unobserved heterogeneity (due to, for example, individual ability, motivation and general taste for education), on the other hand, is the portion of the earnings variance which is known to – and acted on by – the individual, but not observed by the researcher. The unobserved heterogeneity is intimately related to private information on potential returns to education possessed by individuals. For example, if a person knows that her personal return from a given education level is particularly high, she will most likely choose that level of education. Disentangling unobserved heterogeneity (which stems from private information) from true uncertainty from the point of view of the agent making the schooling decision is instrumental when studying income uncertainty.

The question of how education affects income uncertainty is also of policy

relevance. If, for example, more educated agents face larger income uncertainty, risk-averse agents might choose less education than would be socially optimal. This would suggest that income transfers supporting higher education are socially beneficial. On the other hand, if the earnings differences within an education group can be explained by unobserved heterogeneity rather than uncertainty, there might be less room for insurance against uncertainty.

This paper studies two interrelated decompositions. First, I correct for self-selection by modeling the selection of education level. Second, I decompose the uncertainty of income into a permanent component, which reflects fixed characteristics of individuals and a transitory component, which reflects idiosyncratic shocks to income streams of individuals. The transitory component is allowed to vary by time and by education level.

I follow Chen (2008) who extends the framework of Roy (1951) into more than two sectors. Chen disentangles potential variance and unobserved heterogeneity from one another, while taking into account the fact that the selection of agents into educational categories is endogenous. Chen estimates her model using data on U.S. males. She finds that the uncertainty-education profile is U-shaped; the most and least educated individuals face the highest income uncertainty. In addition, according to her model, unobserved heterogeneity is estimated to be up to 20 percent of the total earnings uncertainty.

The dependent variable in Chen's paper is average hourly wage. Her approach disregards perhaps the most important source of earnings uncertainty; namely, the risk of unemployment. Instead of hourly wages, this paper studies yearly total taxable income, which, in addition to income from employment, includes unemployment benefits and other taxable transfers. This measure arguably gives a more complete picture of the income uncertainty related to a level of education. This is particularly relevant because international evidence suggests that differences in unemployment risks between education groups are substantial (e.g. Guiso et al., 2002) and have widened in recent decades (Acemoglu & Autor, 2011). Using total taxable income as the measure of income also mitigates the problem of endogenous selection into employment, as people are observed even if they are not working. The model presented in this paper is estimated using Finnish data. An attractive feature of the Finnish tax code for the current purposes is that virtually all of the income transfers, including unemployment benefits, are taxable and are therefore observed.

I also depart from Chen's approach in another way. Namely, I estimate

separate models for men and women. In most similar studies attention is limited to men, because female workforce participation in most countries has been much lower until recent years. Nonetheless, the female workforce participation in Finland has been similar to male workforce participation already from the 1990s, which warrants doing a similar analysis also for females. Furthermore, since both female education and female workforce participation has also increased internationally, I find that calculating comparable measures for males and females is also interesting in its own right from an international perspective. As a result, I am able to test whether there are differences in the amount of uncertainty in career paths between men and women.

To ensure that the schooling and income equations are jointly identified, an appropriate instrument, which affects schooling but does not appear in the income equation, is needed. I use local differences in supply of education proxied by the region of residence in youth as an instrument. Even though I am able to control for a wealth of family background and individual characteristics, endogeneity of the instrument can not be ruled out. It turns out, that even an analysis using a possibly endogenous instrument is informative.

The association between mean earnings and its variance has been studied, among others, by Palacios-Huerta (2003), Hartog & Vijverberg (2007), Diaz-Serrano et al. (2008a), Schweri et al. (2011), and Koerselman & Uusitalo (2014). The aforementioned papers do not find any robust relationship between education group income means and variances. This might be partly related to the fact that none of these papers address the possible selection effects.

In addition, current paper nests two other prominent research themes. First, I explicitly allow for heterogeneity in the return to education. In this sense, the approach of paper is related to models used to study heterogeneous returns to schooling (e.g. Aakvik et al. 2010, Abadie et al. 2002 and Nybom 2014). Second, the approach chosen here is tangents Cunha et al. (2005) who study how the private information of individuals is related to their choice of education, but do not discriminate between permanent and transitory components. The model of Chen (2008) is also applied in Mazza & van Ophem (2010) and Mazza et al. (2011).

As a preview of the results, I find that income uncertainty decreases up to the tertiary level of education. University educated individuals face slightly larger earnings uncertainty compared to people with a tertiary level education.

For men, however, this effect is not distinguishable from zero. In addition, men face higher income uncertainty than women regardless of their education levels. Moreover, the estimates for the role of unobserved heterogeneity are found to be very small compared to estimates from the U.S.

The rest of this paper is structured as follows: Section 3.2 presents the details of the Finnish schooling system. Section 3.3 introduces the empirical model. Section 3.4 presents the data used. Section 3.5 presents the first and second stage estimates. In addition, Section 3.5 studies the robustness of the results to relaxation of parametric assumptions. I present the uncertainty estimates, compare them to the results acquired using data from the U.S. and discuss how possible endogeneity of the instrument affects the interpretation of the results in Section 3.6. Section 3.7 concludes the paper.

3.2 Brief description of the education system in Finland

The Finnish system of education consists of three stages. The first stage is compulsory education (9 years), which gives eligibility to apply for a secondary education. Secondary education (3 years) is provided by academically oriented upper secondary and vocational secondary schools. After completing secondary education, people apply to tertiary education (3-5 years), which is offered in universities (master's level) and polytechnic colleges (lower tertiary level).¹

There are two stages of selection. First one takes place after comprehensive school when students are about 16 years old. Students have an opportunity to apply to an academically oriented upper secondary school or to a more practically oriented vocational school. The second stage of selection takes place when people apply for tertiary education. In addition to upper secondary school graduates, also vocational school graduates are allowed to apply for tertiary education.

Tertiary education is offered in universities and polytechnic colleges. The focus of universities is research whereas polytechnic colleges are more practi-

¹Finnish universities went through a degree reform in 2005. The reform re-introduced an intermediate bachelor's degree mandatory to all master's level students. This reform does affect this paper because the university graduates observed in the data were already in the labour market by 2005.

cally oriented. Graduates from polytechnics are able to apply to universities to continue their studies. There are no tuition fees at any level. In addition, a student benefit of roughly EUR 400 monthly is offered to students over 18 not living with their parents.

I use a categorical education measure, S_i , with four distinct categories to capture the salient features of the Finnish education system. Each individual i , is placed into one of the schooling categories, which are

- $S_i = 1$; compulsory education,
- $S_i = 2$; secondary education (both vocational and upper),
- $S_i = 3$; lower tertiary education,
- $S_i = 4$; university level education.

As the data does not allow me to identify dropouts, I classify people according to their highest completed level of education.

3.3 Empirical model

3.3.1 Model for potential incomes

This section introduces the empirical model used in this paper. The setup is adopted from Chen (2008). It is an extension of the classic Roy (1951) model into more than two sectors.

The stylized model consists of two periods. In the first period, individuals choose their levels of education according to their tastes. In the second period, they face a yearly income stream which depends on the level of education they have chosen and get an income stream which depends on personal characteristics (both observed and unobserved), the education level chosen and time specific transitory and permanent shocks. I observe a panel of N workers over T years. In the first observation year each worker has already chosen and completed their preferred level of education. The log-income of person i with schooling s in year t is given by

$$y_{it} = y_{1it}I(S_i = 1) + y_{2it}I(S_i = 2) + y_{3it}I(S_i = 3) + y_{4it}I(S_i = 4), \quad (3.1)$$

where $I(\cdot)$ is an indicator function having a value of 1 if $S_i = s$ ($s = 1, 2, 3, 4$) and 0 otherwise. The potential income formulated in (3.1) gives rise to an income regression equation of the form:

$$y_{sit} = \alpha_s + x_{it}\beta + \sigma_s e_{si} + \psi_{st}\varepsilon_{it}, \quad \forall S_i = s. \quad (3.2)$$

In (3.2), α_s is the education-level specific intercept and x_{it} is a vector of observables. The error term in (3.2) consists of two parts. Time invariant fixed effects are incorporated in $\sigma_s e_{si}$. $\psi_{st}\varepsilon_{it}$ denotes transitory shocks, which are assumed to be uncorrelated with both of the observable characteristics and the fixed effect. Both error terms are standard normally distributed and the variances permanent and transitory shocks are scaled by σ_s and ψ_{st} respectively.

Potential earnings variance within a schooling level in year t is therefore $\sigma_s^2 + \psi_{st}^2$. Variation in σ_s^2 is the variance of individual specific fixed effects that are constant in time but may vary across schooling levels. $\psi_{st}\varepsilon_{it}$, on the other hand, may vary with both time and schooling level.

It is assumed, that each individual chooses her level of education according to their preferences. This is formalized by a standard latent index model

$$S_i^* = z_i\theta + v_i, \quad (3.3)$$

where S_i^* represents the optimal level of schooling chosen by individual i . The latent schooling factor v_i is a $N(0, 1)$ random variable. It summarizes the private information such as taste for education and unobservable ability, which are known to the individual but unobservable to the researcher.² z_i contains the elements in vector x_i and an instrument, which is assumed only to affect level of education but not income.

The realized schooling level S_i depends on S_i^* by

$$\begin{aligned} S_i &= 1 & \text{if } -\infty < z_i\theta + v_i \leq \kappa_1, \\ &\vdots \\ S_i &= 4 & \text{if } \kappa_4 \leq z_i\theta + v_i < \infty. \end{aligned} \quad (3.4)$$

The cutoff value, $a_s = \kappa_s - z_i\theta$, is the minimal level of the unobserved schooling factor for which individuals choose s .

²In particular, v_i is assumed to capture both pecuniary and non-pecuniary utility components.

Model has three unobservable elements, e_{si} , ε_{it} and v_i . They are assumed to be jointly normal with the structure

$$\begin{bmatrix} e_{si} \\ \varepsilon_{it} \\ v_i \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & \rho_s \\ 0 & 1 & 0 \\ \rho_s & 0 & 1 \end{bmatrix} \right), \quad (3.5)$$

where $\rho_s \in [-1, 1]$. Intuitively (3.5) implies that the unobservables in the schooling equation may be correlated with permanent earnings differences, but they are assumed to be uncorrelated with the transitory shocks. Therefore, the possible selection bias only contaminates the estimation of the permanent component. The transitory component captures macroeconomic shocks and institutional changes which affect all individuals symmetrically and are therefore uncorrelated with v_i . The structure of the unobservables is assumed to be common knowledge³.

Correlation between the fixed effect and the unobserved schooling factor ρ_s has a central role in the model: it captures the selection effect. If $\rho_s > 0$, the unobservables in schooling and earnings equations are positively correlated, the selection effect is positive and workers with high income potential get more education. If $\rho_s < 0$, people with high income potential tend to enter labor markets at a younger age. Consequently, ρ_s also governs the magnitude and the direction of the bias in the OLS estimates: if $\rho_s > 0$, OLS overstates the true return to education and if $\rho_s < 0$, OLS understates the true return to education.⁴

From the point of view of an individual making her schooling decision, the expected log-income is given by

$$E[y_{sit} \mid s_i = s, x_{it}, v_i] = \alpha_s + x_{it}\beta + \sigma_s \rho_s v_i, \quad (3.6)$$

where the term $\sigma_s \rho_s v_i$ represents the channel through which individual schooling factors affect potential earnings.

³The assumption of common knowledge of shock parameters is needed for the subsequent analysis. Even though this assumption might seem unrealistic, results from survey data (e.g. Schweri et al., 2011 and Webbink & Hartog, 2004) and structural models (e.g. Charles & Luoh, 2003) support the assumption that students have at least some knowledge of their potential post-schooling income.

⁴Cameron & Heckman (1998) discuss, which types of economic models would rationalize the ordered structure given by Equations (3.3), (3.4) and (3.5). Most importantly, they conclude that v_i has to be independent of the level of schooling, i.e. $v_{si} = v_i \forall s$.

Since the agents are assumed to know their draw of v_i , the measure of income uncertainty should account for it. By equations 3.2 and 3.5 the uncertainty for schooling level s reads as:

$$\begin{aligned}\tau_{st}^2 &= Var [\sigma_s e_{si} + \psi_{st} \varepsilon_{ei} \mid x_{it}, S_i = s, v_i] \\ &= \sigma_s^2 (1 - \rho_s^2) + \psi_{st}^2.\end{aligned}\tag{3.7}$$

Equation (3.7) can be rearranged to $\sigma_s^2 + \psi_{st}^2 = \sigma_s^2 \rho_s^2 + \tau_{st}^2$. It shows that the residual variance of equation (3.2) consists of two parts: unobserved heterogeneity ($\sigma_s^2 \rho_s^2$) and uncertainty (τ_{st}^2). Income uncertainty is governed by the permanent and transitory components (σ_s and ψ_{st}) and the correlation between the unobserved schooling factor and permanent component ρ_s .

3.3.2 Identification of variance components

Equations (3.6) and (3.7) are not directly applicable for regression analysis because v_i is unobservable. To account for the effect of unobserved v_i , a multi-choice version of the Heckman selection correction model (Heckman, 1979) is used.

As a first stage, a latent index model (3.3) is estimated using ordered probit. The model is used to calculate generalized residuals of the schooling model⁵,

$$\lambda_{si} = \frac{\phi(\kappa_s - z_i \theta) - \phi(\kappa_{s+1} - z_i \theta)}{\Phi(\kappa_{s+1} - z_i \theta) - \Phi(\kappa_s - z_i \theta)},$$

where $\phi(\cdot)$ is the probability density function of a standard normal distribution and $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution. Adding λ_{si} as a regressor to (3.6) accounts for the correlation between unobserved schooling factor and education level. The expected value of observed earnings from the point of view of the researcher can now be written as

$$E[y_{sit} \mid s_i = s, x_{it}, z_i] = \alpha_s + x_{it} \beta + \sigma_s \rho_s \lambda_i.\tag{3.8}$$

Calculating the difference between realized and expected earnings gives

$$y_{sit} - E[y_{sit} \mid s_i = s, x_{it}, z_i] = \sigma_s e_{si} - \sigma_s \rho_s \lambda_i + \psi_{st} \varepsilon_{sti},\tag{3.9}$$

⁵In the case of a binary schooling variable, generalized residuals would reduce to Inverse Mills' ratios.

whose variance reads as

$$Var[y_{sit} | s_i = s, x_{it}, z_i] = \sigma_s (1 - \rho_s^2 \delta_{si}) + \psi_{st}^2 \quad (3.10)$$

(3.10) implies that whenever $\rho_s \neq 0$, selection leads to a truncation of the observed income distribution which, in turn, leads to an understatement of income variance compared to the case we would observe if education was randomly assigned to individuals. The degree of understatement is given by ⁶:

$$\delta_{si} = \lambda_{si}^2 - \frac{(\kappa_s - z_i \theta) \phi(\kappa_s - z_i \theta) - (\kappa_{s+1} - z_i \theta) \phi(\kappa_{s+1} - z_i \theta)}{\Phi(\kappa_{s+1} - z_i \theta) - \Phi(\kappa_s - z_i \theta)}.$$

The variance of transitory component can be identified from the residuals of the within-individual model,

$$(y_{it} - \bar{y}_i) = (x_{it} - \bar{x}_i) \beta - (\xi_{sit} - \bar{\xi}_{si}), \quad (3.11)$$

where bars denote time averages of the corresponding variables (note that time-invariant individual regressors, including λ_{si} , are subsumed in the fixed effects) and $\xi_{sit} = \psi_{st} \varepsilon_{sit}$. The procedure for estimating $\hat{\psi}_{st}^2$ is discussed in detail in the Appendix.

The regression coefficients $\hat{\alpha}_s, \hat{\beta}$ and $\rho_s \hat{\sigma}_s = \hat{\gamma}_s$ can be identified using a between-individuals model

$$\bar{y}_{si} = \alpha_s + \bar{x}_i \beta + \gamma_s \lambda_{si} + \omega_i. \quad (3.12)$$

The error term in (3.12) is, by equation (3.9),

$$\omega_i = \sigma_s \varepsilon_{si} + \bar{\xi}_{si} - \gamma_s \lambda_{si},$$

and its variance is

$$Var[\omega_i | S_i = s, \bar{x}, z] = \sigma_s^2 - \gamma_s^2 \delta_{si} + \frac{\psi_{st}^2}{T},$$

Solving this for σ_s^2 gives the estimator for time invariant individual specific variance of earnings for each schooling level,

$$\hat{\sigma}_s^2 = \widehat{Var}[\omega_i | S_i = s, \bar{x}, z] + \hat{\gamma}_s^2 \bar{\delta}_s - \frac{\psi_{st}^2}{T}, \quad (3.13)$$

where, again, bars denote averages over individuals. The second term $\hat{\gamma}_s^2 \bar{\delta}_s$ in equation (3.13) is needed to correct for the truncation of variances due to self selection. Each term in equation (3.7) is now identified:

$$\hat{\tau}_{st}^2 = \hat{\sigma}_s^2 - \hat{\gamma}_s^2 + \hat{\psi}_{st}^2 \quad (3.14)$$

⁶ λ_i and δ_i are derived in Maddala (1987) under the assumption of joint normality.

3.4 Data

The data used in this paper is a random sample of 46321 individuals from a Finnish Census. I limit my attention to working males and females aged between 28 and 43. I assume that by the age of 28, people have finished their education. An educational category of an individual is defined as the education they have at the youngest age they are observed in the panel. It is possible that individuals educate themselves further after the age of 28, but as my main interest is, how well individuals are able to predict their income in their youth, I interpret individuals' decision to re-educate themselves at later ages as a realized uncertainty, which should not be controlled for.⁷

The panel spans 1994-2009, adding up to a total of 244637 individual-year observations for men and 213840 for women. The composition of the sample is summarized in Table 3.1. The panel is constructed in a way that even the youngest cohort is observed for six years. I have limited my attention to individuals who were born after 1966 to make sure that an educational reform which took place in Finland in the early 1970's does not differently affect the cohorts under study.⁸

The educational categories are defined according to the standard classification of education⁹.

Since the goal of this paper is to study the returns to completing a degree rather than degree major, I do not discriminate between fields of education but only levels. The specification used allows the marginal return to schooling to vary according to the level of schooling completed. Using the highest degree attained also mitigates the effect of measurement errors, since years of education are usually imputed using average years of education needed to complete a degree, which introduces measurement error.

⁷In practice this is rather rare. Only roughly five percent of individuals in the lowest education category get a higher degree during the time in the panel. For higher education categories, the proportion of people who re-educate themselves are in the order of 1 percentage.

⁸The goal of this reform was to standardize the quality of comprehensive education within the country. Consequently, people born before 1966 had a different school system from those born after 1966. In particular, before the reform, the quality of comprehensive education varied a great deal between regions. In addition, the reform resulted in removal of one educational tracking stage. For details about the reform, see e.g., Pekkarinen et al. (2009).

⁹Available from www.stat.fi/meta/luokitukset/koulutus/001-2010/index_en.html

As already mentioned, the risk of unemployment constitutes a considerable part of the total income uncertainty. Choice of the outcome variable reflects this: dependent variable in income regressions is the log of total yearly taxable income which, in addition to wages and entrepreneurial income, includes taxable income transfers but excludes income from capital gains. As a result, the observed income streams allow for potential spells of unemployment.¹⁰ However, if a person drops out of the workforce entirely, she only contributes to the estimation for the years when she is either unemployed or working. The variance of yearly total income is, by definition, comprised of three components, hourly wage, hours worked and income transfers from the social insurance system. Consequently, unless the covariances of the three components are very large and negative, the total variances will be higher than the variance of hourly wages (see, e.g. Abowd & Card 1989).¹¹

Income concept may introduce a problem of its own, since not working may be either voluntary or involuntary. To separate the involuntarily unemployed from voluntary workforce non-participants I include only the observations where the main type of activity of an individual is either working or unemployed in the estimation¹². For example, if a person is on a parental leave for one year, but is either working or unemployed for nine years, she contributes to the estimation for the nine years when she is not on a maternity leave.

The approach chosen leaves some (likely mis-classified) observations with zero income. I omit these observations. This does not affect the main results, because the proportion of zero-observations is very small (less than 2% of observations)¹³. To ensure comparability between years, the measure of income is deflated to EUR 2009 using the Consumer Price Index.

I do not have a reliable information on whether workers are part-time or full-time. Therefore, to some extend, the uncertainty measures also reflect

¹⁰Also the (former) self-employed individuals are entitled to unemployment transfers.

¹¹Low et al. (2010) discuss a model which separates individual productivity and firm-worker match specific unemployment risks from one another in a structural framework. The dependent variable in this paper, total taxable income, should be interpreted as a combination of productivity and match specific uncertainty, but measuring the respective contributions of these two is beyond the scope of this paper.

¹²In general, for an individual to be classified as unemployed (and be eligible for unemployment benefits), she must agree to accept a job if offered one.

¹³None of the results change substantially whether I exclude them or impute a small positive income value for these observations.

voluntary part-time work. Nonetheless, the proportion of part-time workers in Finland is rather small in comparison to most developed countries. The share of part-time workers is of total work force was 9.2% for men and 16.9% for women. Further, working part-time is virtually nonexistent in professional and management positions (where most people likely are in education categories 3 or 4) (Eszter, 2011).

The vector of controls in Equation (3.2) includes paternal and maternal education classified using the same four-level classification which is used for individuals' own education, a measure for family income calculated as the sum the income of mother and income of father and nine dummies for family socioeconomic status. Family background characteristics are measured at age 14 if possible. In addition, controls for first language, nationality and the region of residence in adulthood are included.

Estimation of Equation (3.12) necessitates an instrument excluded from the income equation (3.2). I use local differences in the supply of education proxied by region of residence in youth as an instrument.^{14,15} The identifying assumption is, therefore, that the region of residence is correlated with individuals' access to higher education but not their post-schooling income after controlling for other observable characteristics. Consequently, I need to exclude individuals who have no information on their place of residence at youth. The estimation results provided in Section 5.1 support the notion that the instrument is relevant.

As discussed by Card (1993), the place of residence in youth may affect income because of differences in local supply of education, but also because family background is correlated with place of residence. I control for family background variables to account for this potential source of endogeneity. In addition, Card points out that differences in comprehensive schooling resources may affect subsequent income. In the case of Finland, comprehensive education is arranged in public schools with very small differences in resources and quality (Kirjavainen, 2009). In addition, international evidence suggests that the impact of school quality on learning (Kramarz et al., 2009) and income (Betts, 1995) is rather small even in the context of less standardized com-

¹⁴Childhood information is collected from censuses. Censuses were administered in 1970, 1975, 1980, 1985 and yearly from 1988 onwards.

¹⁵A similar instrument is used, among others, by Card (1993) for schooling choices in the U.S., Bedi & Gaston (1999) for schooling choices in Honduras and Lindqvist & Vestman (2011) for occupation choices in Sweden.

Table 3.1: Sample sizes used in estimation.

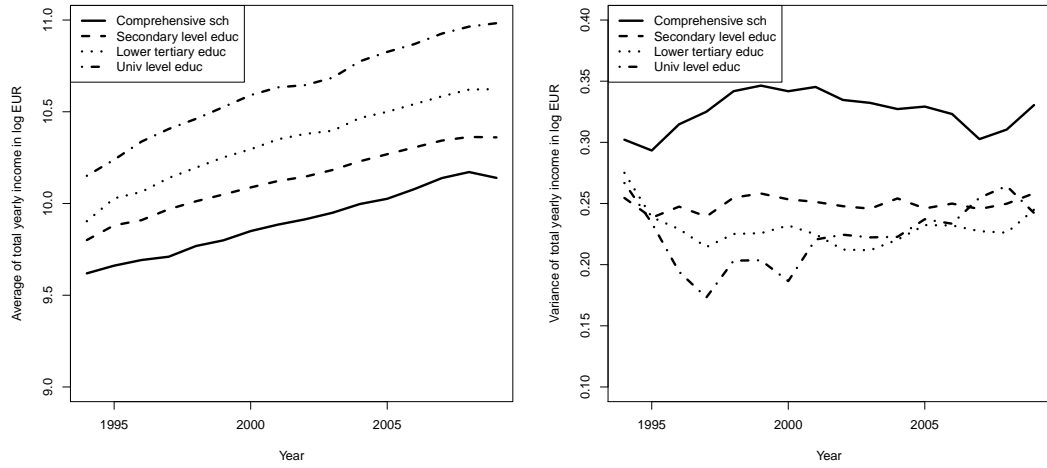
| Year of birth | Sample size (men) | Sample size (women) | Year-obs. (men) | Year-obs. (women) | Years |
|---------------|----------------------|------------------------|--------------------|----------------------|-----------|
| 1966 | 2742 | 2543 | 38576 | 33335 | 1994-2009 |
| 1967 | 2696 | 2510 | 35330 | 30382 | 1995-2009 |
| 1968 | 2530 | 2501 | 31253 | 28601 | 1996-2009 |
| 1969 | 2318 | 2213 | 26752 | 23623 | 1997-2009 |
| 1970 | 2417 | 2211 | 25729 | 21475 | 1998-2009 |
| 1971 | 2118 | 2155 | 20589 | 19216 | 1999-2009 |
| 1972 | 2134 | 2056 | 18905 | 16643 | 2000-2009 |
| 1973 | 2100 | 1928 | 16462 | 13915 | 2001-2009 |
| 1974 | 2226 | 2146 | 15612 | 13739 | 2002-2009 |
| 1975 | 2492 | 2285 | 15429 | 12911 | 2003-2009 |
| Total | 23773 | 22548 | 244637 | 213840 | |

prehensive schooling systems. Finally, to control for differences in local labor market conditions in the presence of imperfect labor mobility, I control for job location in adulthood in the income equation. Despite controlling for family background and job location characteristics, it might still be the case that the instrument is correlated with the outcome. If this is the case, the estimates for ρ_s overestimate the true parameter value. I discuss this possibility in Section 6.

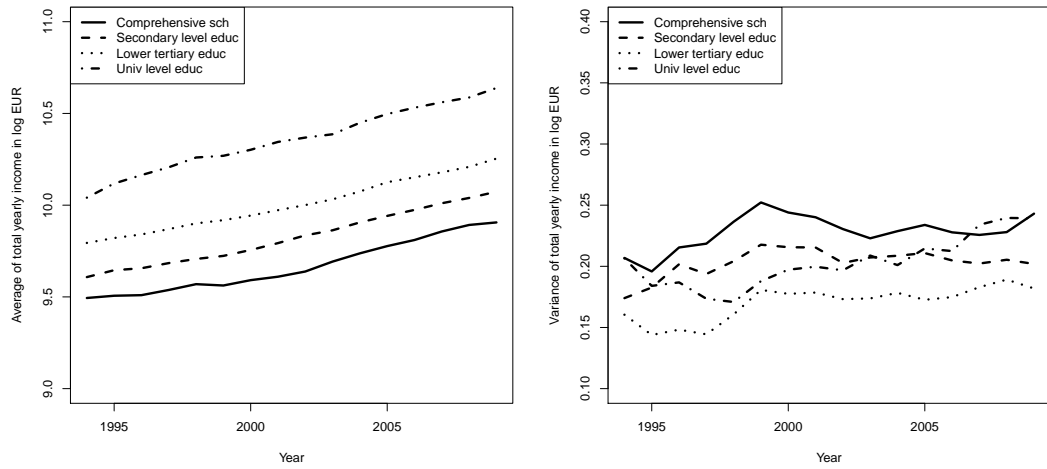
Figure 3.1 plots the estimated averages and standard deviations of log incomes for each panel year calculated from the sample described in Table 3.2. It is apparent that the mean income rises with education. Differences in the standard deviations of incomes are quantitatively much smaller, but some aspects can already be noted. First, people with only a compulsory education have the largest standard deviations of incomes. The standard deviation of male income in the lowest education category is especially large. The relative contribution of heterogeneity, permanent differences and transitory differences remains unclear. Using the method outlined in the previous section, it is possible to disentangle them from one another

Control variables, which capture the observed heterogeneity, are summarized in Table 3.2. Not surprisingly, the distribution of family background variables is virtually identical between sexes. There are larger differences in the distribution of education levels. The proportion of men with a basic or secondary education is larger than women. Conversely, there are more women with at least a tertiary level education.¹⁶

¹⁶The fact that women have overtaken men in terms of their education is a common finding in most industrialized countries (Barro & Lee, 2010).



(a) Men



(b) Women

Figure 3.1: Means (left panel) and variances (right panel) of yearly incomes by year for men and women.

Table 3.2: Descriptive statistics of the explanatory variables.

| <u>Time invariant variables</u> | | Men | Women | <u>Family background</u> | | Men | Women |
|----------------------------------|--|------------------|------------------|--|--|--------------------|---------------------|
| <i>Education</i> | | | | <i>Father's education</i> | | | |
| Compulsory education | | 0.18 (0.38) | 0.15 (0.36) | Compulsory education | | 0.53 (0.5) | 0.53 (0.5) |
| Upper secondary | | 0.52 (0.50) | 0.45 (0.5) | Upper secondary | | 0.25 (0.43) | 0.25 (0.43) |
| Lowest tertiary | | 0.21 (0.41) | 0.25 (0.43) | Lower tertiary | | 0.15 (0.36) | 0.15 (0.36) |
| Bachelor or more | | 0.09 (0.29) | 0.16 (0.37) | University | | 0.06 (0.24) | 0.06 (0.24) |
| <i>First language</i> | | | | <i>Mother's education</i> | | | |
| Finnish | | 0.950 (0.218) | 0.951 (0.216) | Compulsory education | | 0.52 (0.48) | 0.52 (0.5) |
| Swedish | | 0.048 (0.215) | 0.048 (0.214) | Upper secondary | | 0.31 (0.46) | 0.31 (0.46) |
| Other | | 0.002 (0.040) | 0.001 (0.032) | Lowest tertiary | | 0.15 (0.36) | 0.15 (0.36) |
| <i>Nationality</i> | | | | Bachelor or more | | 0.03 (0.17) | 0.03 (0.17) |
| Finnish | | 0.998 (0.042) | 0.999 (0.032) | | | | |
| Other | | 0.002 (0.042) | 0.001 (0.032) | | | | |
| | | | | <i>Family income (in 100 EUR 2009)</i> | | 394.23 (253.06) | 393.401 (253.01) |
| | | | | <u>Average ages in years</u> | | | |
| | | | | 1994 | | 28 | 28 |
| | | | | 1997 | | 30 | 30 |
| | | | | 2000 | | 31 | 31 |
| | | | | 2003 | | 33 | 33 |
| | | | | 2006 | | 36 | 36 |
| | | | | 2009 | | 39 | 39 |
| <u>Instrument for education</u> | | | | | | | |
| <i>Region residence in youth</i> | | | | | | | |
| Uusimaa | | 0.20 (0.40) | 0.21 (0.41) | Pohjois-Karjala | | 0.03 (0.17) | 0.04 (0.2) |
| Varsinais-Suomi | | 0.08 (0.27) | 0.08 (0.27) | Keski-Suomi | | 0.05 (0.22) | 0.05 (0.22) |
| Satakunta | | 0.05 (0.22) | 0.05 (0.22) | Etelä-Pohjanmaa | | 0.05 (0.22) | 0.05 (0.22) |
| Kanta-Häme | | 0.03 (0.17) | 0.03 (0.17) | Pohjanmaa | | 0.04 (0.2) | 0.03 (0.17) |
| Pirkanmaa | | 0.08 (0.27) | 0.08 (0.27) | Keski-Pohjanmaa | | 0.02 (0.14) | 0.02 (0.14) |
| Päijät-Häme | | 0.04 (0.2) | 0.04 (0.2) | Pohjois-Pohjanmaa | | 0.08 (0.27) | 0.07 (0.26) |
| Kymenlaakso | | 0.04 (0.2) | 0.04 (0.2) | Kainuu | | 0.02 (0.14) | 0.02 (0.14) |
| Etelä-Karjala | | 0.03 (0.17) | 0.03 (0.17) | Lappi | | 0.05 (0.22) | 0.05 (0.22) |
| Etelä-Savo | | 0.03 (0.17) | 0.04 (0.2) | Itä-Uusimaa | | 0.02 (0.14) | 0.02 (0.14) |
| Pohjois-Savo | | 0.05 (0.22) | 0.05 (0.22) | | | | |

Notes: Standard deviations in parentheses. Calculations are based on a random sample of individuals who are born between 1966–1975 and are between 28 and 43 years old. N is the sample size of time-invariant variables. Year-observations report the average number of years an individual is observed in the data.

3.5 First and second stage estimates

3.5.1 First stage: schooling choice

Equation (3.3) is estimated by an ordered probit. The estimated model includes family background measures and the instrument for education. Table 3.3 shows the test statistics for the relevance of the instruments (joint significance of the region dummies). The relevance of instrument using linear education as the dependent variable is also reported because there are no rule-of-thumb test statistic values for the relevance of instruments in maximum likelihood models.

Education categories are converted to years of education using average times-to-degree measured in full years.¹⁷ This introduces noise to the dependent variable. Consequently F-statistics reported in Table 3.3 might represent a lower bound for the effect of the instruments on education. Nonetheless, even the F-statistics of the linear model suggest that the instruments are highly relevant.

Table 3.3: Test statistics for relevance of instrument.

| | | | |
|--|----------------------------|---------------------|---------------------|
| <i>Dependent variable: categorical education</i> | Likelihood ratio statistic | Men | Women |
| | | 334.66*** [0.00] | 417.06*** [0.00] |
| <i>Ordered probit</i> | | | |
| <i>Dependent variable: education in years</i> | F-statistic | 17.06*** | 22.74*** |
| | | [0.00] | [0.00] |
| <i>Linear model</i> | | | |

Notes: P-values in brackets. Instrument for education is the region of residence in youth. Both models include controls for parents' education, family income, nationality, first language and year of birth.

Significance levels in all regressions: *** 0.1%, ** 1%, * 5% and . 10%.

3.5.2 Second stage: average returns to schooling

This section presents estimates for the average returns to education. The reported estimates are based on the between model (3.12), where average yearly income of an individual is regressed on individual characteristics, schooling variable, mean age, mean age squared and the generated regressor λ_{si} .

¹⁷These are 9 years for the compulsory level, 12 years for the secondary level, 15 for the lower tertiary education and 17 for the master's level education.

To account for the fact that λ_{si} is a generated regressor, the standard errors are calculated using a block bootstrap procedure, where 200 samples of size N are drawn with replacement from the original population. For each bootstrap draw k , the estimates $\hat{\alpha}_s^k, \hat{\beta}^k$ and $\hat{\gamma}_s^k$ are calculated. Expected values and standard errors of the parameters are calculated from the distribution of these bootstrap draws.

The parameter estimates and their standard errors are presented in the second column of Table 3.4. The effect of education on income is nonlinear with respect to level of education. Most educated individuals accrue the highest marginal returns.

To facilitate comparability to previous literature on monetary returns to education, also IV estimates for the average return to education are reported in the fourth column of Table 3.4. They are reported for reference, but are not used when estimating uncertainty parameters. The IV estimates are somewhat larger than the corresponding estimates based on the selection model.

Without selectivity correction, the positive correlation between schooling of individuals and the residual in the income equation would result in an upward bias in the estimated returns to income. This bias arises if some of the unobservable characteristics (a high draw of e_{si}) are positively correlated with the schooling choice of an individual. This happens, for example, if the people with high income potential are also those who self-select into higher education (Griliches, 1977).

In the context of the current model, the correlation between income and schooling presents itself in positive values of the correction term γ_s . There is limited evidence of this: for men the estimate of the correction terms for lowest education categories γ_1 and γ_2 are positive and statistically significant. For women, the correction term for the highest education category γ_4 are statistically significantly positive. The correction terms for other levels of schooling are not statistically distinguishable from zero at conventional levels. Even the correction terms that differ statistically significantly from zero are economically rather small.¹⁸

Quantitatively small estimate for $\hat{\rho}$, suggests that the unobservable hetero-

¹⁸The fact that OLS and two-stage estimates are very close to one another, is a classic sign of a weak instruments issue (e.g. Bound et al. 1995). Notice, however that the first stage results point to instruments being highly relevant. The possibility that instruments are invalid, or correlated with the outcome, is discussed in more detail in Section 6.3.

geneity for each education level is very small. This suggests that, either, individuals have very little private information on their comparative advantages not captured by the observable characteristics, or, alternatively, individuals do not act on their private information on potential incomes.

A possible concern for the validity of the results of this paper is that they hinge on the assumption of joint normality of error terms and the linear dependence between mean incomes and the selection term. To shed some light on this concern, I have performed the test described in Vella (1998, pp. 137-138) and estimated Equation (3.12) where in addition to the Inverse Mills' Ratio, second and third degree polynomials of the Inverse Mills' Ratios are used as regressors. This allows me to test for possible deviations from joint normality of unobservables in schooling and income equations. The tests for the joint significance of the higher order polynomial always fail to reject the null hypothesis of linearity. This speaks in favor of the assumption of the joint normality.

Confidence in the distributional assumptions is further strengthened by the fact that the estimates of $|\hat{\rho}| < 1$ and $\hat{\delta}_{si} \in [0, 1]$ for all individuals, which is consistent with normality (notice that no restrictions on $\hat{\rho}$ and $\hat{\delta}$ are placed). Nonetheless, even though the assumption of normality is not immediately rejected, some caution should be exercised when interpreting the results, since they obviously rely on ultimately non-testable distributional assumptions.

Table 3.4: Second stage estimates.

| Men | Education categories <i>Education</i> | | | Years of education | |
|-------|--|-------------------|-------------------------|--------------------|-------------------|
| | | OLS | Corrected for selection | OLS | IV |
| | Secondary educ. | 0.25*** (0.01) | 0.25*** (0.04) | 0.09*** (0.01) | 0.13*** (0.01) |
| | Lower tertiary educ | 0.47*** (0.01) | 0.45*** (0.04) | | |
| | University | 0.74*** (0.01) | 0.73*** (0.07) | | |
| | <i>Selection correction term</i> | | | | |
| | Compulsory educ. | | 0.03** (0.01) | | |
| | Secondary educ. | | 0.02* (0.01) | | |
| | Lower tertiary | | 0.01 (0.02) | | |
| | Bachelor or more | | 0.01 (0.03) | | |
| | | | | | |
| Women | Education categories <i>Education</i> | | | Years of education | |
| | | OLS | Corrected for selection | OLS | IV |
| | Secondary educ. | 0.22*** (0.01) | 0.19*** (0.04) | 0.08*** (0.01) | 0.11*** (0.04) |
| | Lower tertiary educ | 0.37*** (0.01) | 0.38*** (0.06) | | |
| | University | 0.77*** (0.01) | 0.72*** (0.07) | | |
| | <i>Selection correction term</i> | | | | |
| | Compulsory educ. | | -0.01 (0.02) | | |
| | Secondary educ. | | 0.00 (0.01) | | |
| | Lowest tertiary | | 0.00 (0.01) | | |
| | Bachelor or more | | 0.04* (0.02) | | |

Notes: Estimates are based on a between-individuals model. Standard errors in parenthesis. For the OLS and IV models, standard errors are based on the heteroskedasticity and autocorrelation consistent OLS covariance matrix. For the selection corrected model standard errors are based on 200 bootstrap replications. In addition to variables reported, both models include controls for parents' education, family income, nationality, first language and year of birth, age and age squared. In columns 1 and 2, the education is measured as a categorical education variable. In columns 3 and 4, the education categories are transformed into years of education using the typical time-to-education measures. Significance levels in all specifications: *** 0.1%, ** 1%, * 5% and . 10%.

3.6 Uncertainty estimates

3.6.1 Main estimates

The estimates for the permanent and transitory components of income uncertainty at each education level are reported in this section. Standard errors of each variance component are again calculated from 200 bootstrap resamples. The uncertainty estimates are reported in Table 3.5. Since the error structure implies that unobserved heterogeneity is not correlated with the transitory shocks, total earnings uncertainty is a sum of the two components: transitory shocks and permanent earnings variance purged from the effects of private information.

I first discuss the transitory variance estimates. Since transitory shocks are time-varying, I start by reporting its time-means (denoted by $\bar{\psi}_s^2$). Among men, individuals in the lowest education group face the highest transitory income shocks. People with at least a secondary level education face similar transitory income shocks regardless of education. The estimation results are almost entirely opposite for women: transitory shock variances are almost constant among the three lowest education categories. The variances of transitory shocks are somewhat higher in the group with the highest education compared to other groups, even though the difference is small. The differences between the transitory shocks of men and women are otherwise rather small, but men with only a basic level education face the highest transitory income shocks. The time-profile of the variance of transitory shocks can be seen from Figure 3.2; they are rather similar between education groups and sexes, which supports the idea that transitory income shocks are mostly driven by macroeconomic conditions in, for example, unemployment and job turnover.

Turning to permanent income variance, I find that education decreases permanent income differences considerably for men; having a secondary degree decreases permanent income uncertainty by 23%. Permanent income uncertainty decreases by another 15% with a tertiary level education. The difference between lower tertiary and university level education are statistically insignificant. In total, the permanent inequality is over 35% larger for the lowest education category in comparison to the highest education category. The effect of education on permanent income variance is of similar magnitude for women and men. Having a secondary level education decreases permanent income variance by 30%. The uncertainty decreases further with a tertiary

level education, but the differences between lower tertiary and university education is indistinguishable from zero for men and small and positive for women. Despite the marginal effects being similar, the level of permanent uncertainty is considerably larger for men than women regardless of the level of education. The differences in permanent incomes are twice as large for men than for women in the two highest education categories. Transitory and total income inequality levels are plotted in Figure 3.3.

To get a better grasp of the effects of education on average return and uncertainty, Figure 3.4 plots the marginal effects of completed education on average income and income uncertainty. Completing a secondary education decreases income uncertainty of men more than that of women. A tertiary level education has a small negative effect on male and female earnings uncertainty. Completing an university level education increases uncertainty somewhat; this effect is, however, statistically significant for men but not for women. The returns-to-degree estimates are similar among men and women on all levels of education.

Table 3.5: Estimates of income variance components.

| | Men | | | |
|---|--------------------|---------------------|---------------------|--------------------|
| | Education category | | | |
| | 1 | 2 | 3 | 4 |
| Variance of transitory shock ¹ | 0.09*** (0.002) | 0.07*** (0.001) | 0.07*** (0.001) | 0.07*** (0.002) |
| Marginal effects ² | | -0.02*** (0.002) | -0.001 (0.002) | 0.001 (0.003) |
| Permanent component ³ | 0.17*** (0.01) | 0.13*** (0.01) | 0.11*** (0.01) | 0.11*** (0.01) |
| Marginal effects ⁴ | | -0.04*** (0.006) | -0.02*** (0.006) | 0.00 (0.01) |
| Effect of private information on permanent component ⁵ | 0.00 (0.06) | 0.00 (0.04) | 0.00 (0.04) | 0.00 (0.06) |
| Total wage uncertainty ⁶ | 0.26*** (0.005) | 0.20*** (0.003) | 0.18*** (0.005) | 0.18*** (0.009) |
| Marginal effects ⁷ | | -0.06*** (0.006) | -0.02*** (0.006) | 0.01 (0.01) |
| | Women | | | |
| | Education category | | | |
| | 1 | 2 | 3 | 4 |
| Variance of transitory shock ¹ | 0.07*** (0.002) | 0.08*** (0.001) | 0.07*** (0.001) | 0.08*** (0.002) |
| Marginal effect ² | | -0.002 (0.002) | -0.002* (0.001) | 0.005** (0.002) |
| Permanent component ³ | 0.10*** (0.004) | 0.07*** (0.002) | 0.05*** (0.002) | 0.05*** (0.005) |
| Marginal effect ⁴ | | -0.03*** (0.005) | -0.03*** (0.003) | 0.01 (0.01) |
| Effect of private information on permanent component ⁵ | 0.00 (0.04) | 0.00 (0.02) | 0.00 (0.02) | 0.00 (0.04) |
| Total wage uncertainty ⁶ | 0.17*** (0.003) | 0.15*** (0.002) | 0.12*** (0.002) | 0.13*** (0.005) |
| Marginal effect ⁷ | | -0.03*** (0.004) | -0.03*** (0.003) | 0.01 (0.05) |

¹ $\bar{\psi}_s^2$

² $\bar{\psi}_s^2 - \bar{\psi}_{s-1}^2$

³ σ_s^2

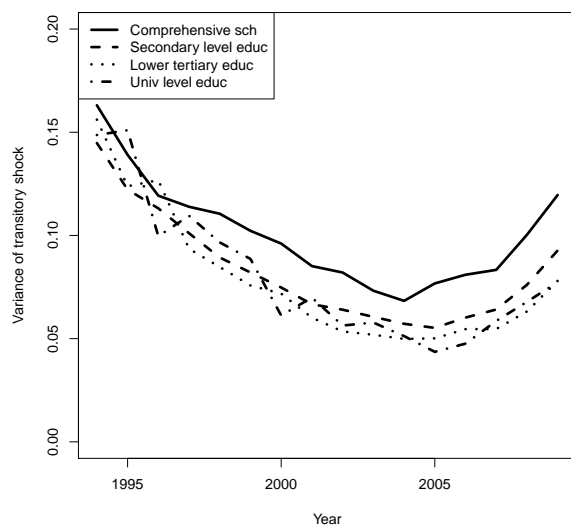
⁴ $\sigma_s^2 - \sigma_{s-1}^2$

⁵ γ_s^2

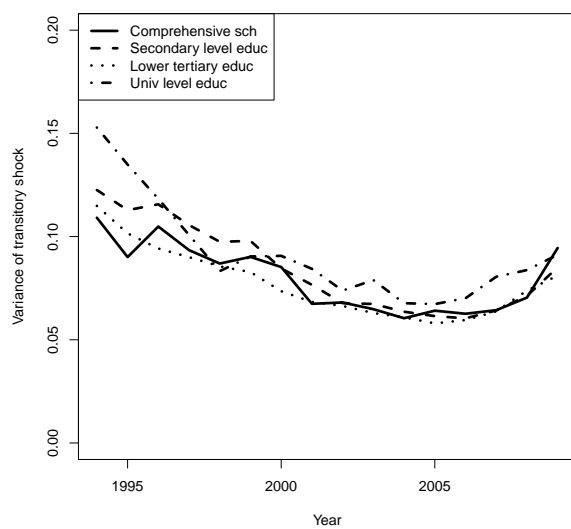
⁶ $\bar{\psi}_s^2 - \gamma_s^2 + \sigma_s^2 = \tau_s^2$

⁷ $\tau_s^2 - \tau_{s-1}^2$

Notes: Variance component decompositions are based on Equation (3.13) with region of residence in youth as an instrument. Standard errors from 200 bootstrap resamples in parenthesis. Education categories are: 1. compulsory education; 2. secondary education; 3. lowest tertiary education; 4. bachelor level education or higher. Significance levels in all specifications: *** 0.1%, ** 1%, * 5% and . 10%.



(a)
Men



(b)
Women

Figure 3.2: Transitory shock variances year by year.

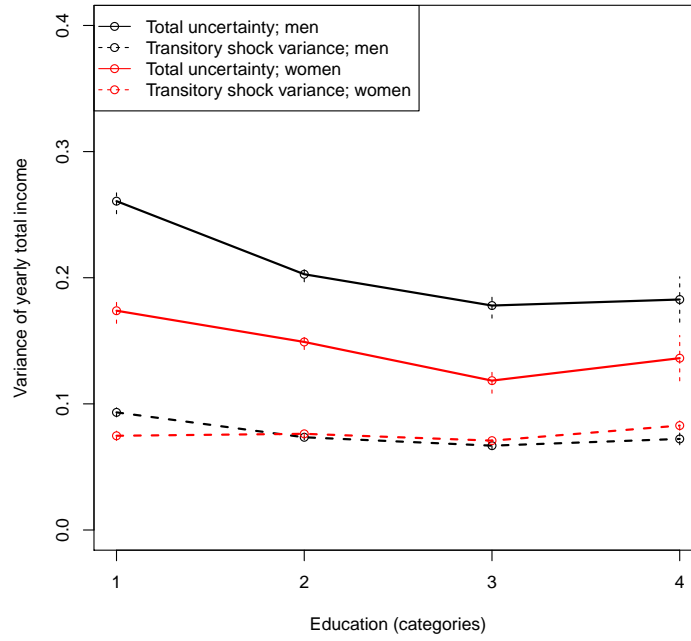


Figure 3.3: Transitory (dashed lines) and total income variances (solid lines) for men and women by education categories. The dashed vertical lines represent 95% confidence intervals calculated by bootstrap. Education categories are: 1. compulsory education; 2. secondary education; 3. lowest tertiary education; 4. bachelor level education or higher.

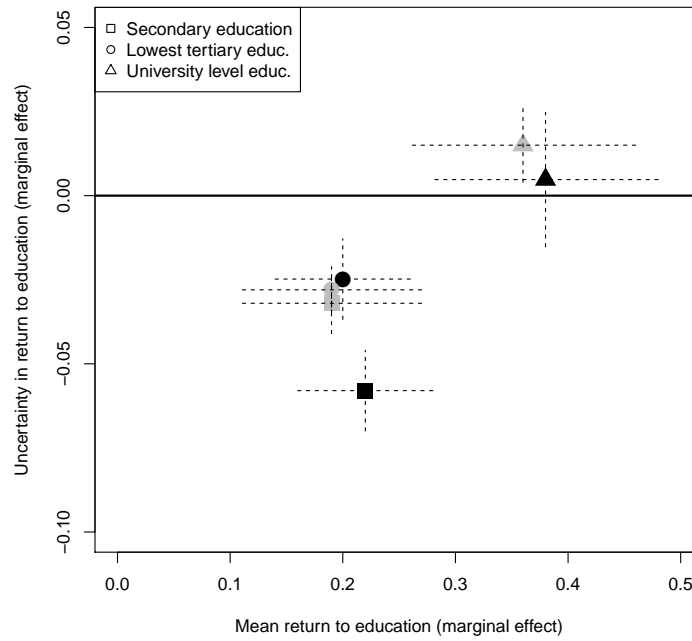


Figure 3.4: Marginal effects of completing a degree on mean income (horizontal axis) and uncertainty (vertical axis) for men (black symbols) and women (gray symbols). The dashed lines represent the bootstrapped 95% confidence intervals of return and uncertainty estimates on the corresponding axes.

3.6.2 Comparison to U.S. studies

My uncertainty estimates differ from those obtained in Chen (2008). Completing an education is found to decrease income uncertainty at lower education levels, but the effect is close to zero or even marginally positive for university graduates, whereas Chen's results suggest a U-shaped profile of income uncertainty where the highest and lowest education categories face the highest income uncertainty. Chen conjectures that the high income uncertainty of university graduates is related to the fact that they are able to choose their occupations from a wider pool of potential occupations, which is also reflected in their permanent income differences. It is possible that also Finnish university graduates are able to choose their occupations from a wider pool, but their income uncertainty is still smaller than that of lower educated individuals. It seems plausible that this is due to smaller risk of unemployment of more educated individuals.

Perhaps a more surprising finding is the very small unobserved heterogeneity. This is in stark contrast to the estimates based on data from the U.S.¹⁹ For example, Cunha & Heckman (2007) conclude that up to 50% of the ex post variance in income of college graduates is attributable to unobserved heterogeneity, i.e. is foreseeable by individuals making their choice on whether or not to attend college. A potential explanation for the results is the choice of measure of income. The studies based on U.S. data use either long period average earnings (Cunha & Heckman, 2007), or average hourly wage (Chen, 2008), which both arguably contain less variation than the yearly total income. Therefore, the correlation between residuals in schooling and income equations, which is used to identify unobserved heterogeneity, is mechanically smaller in absolute value.

A second partial explanation is that I target people in their youth. As the nine-year comprehensive school is mandatory, it may indeed be the case that young people making their choice on whether or not to attend higher education have limited information on their future incomes at the age of fifteen. In addition, early-career earnings are usually more volatile, or more uncertain.

¹⁹Mazza et al. (2011) attempts to replicate the results in Chen (2008) using the same data but a different instrument, but they get very different results. In particular, their estimates for the unobserved heterogeneity are almost indistinguishable from zero regardless of education level and that the length of education and uncertainty are positively correlated. The same model applied to British data shows uncertainty decreasing with education and very small unobserved heterogeneity, while German data do not fit the model at all.

Since the Finnish comprehensive education is extremely standardized and allows for little differentiation in school curricula between skill groups, it may convey less private information to students about their future incomes and, therefore lead to a smaller unobserved heterogeneity, than a less standardized system would.²⁰

However, even though the unobserved heterogeneity is found to be smaller than in the U.S., this does not necessarily imply that people would have less information on their potential future income streams. Rather, it seems plausible, that, given the high amount of redistribution and collective bargaining in the Finnish labor market, people would have a rather good perception on their potential future income, but this perception is not correlated with individual characteristics which are unobservable to the econometrician.

3.6.3 Sensitivity of results to the instrument

Even though I control for a variety of background characteristics in both the first and second stages, the validity of the instrument is somewhat questionable. It is possible that the instrument has a direct effect on income even after controlling for the elements of x .

To test for this possibility, I do a following falsification test suggested in Bound et al. (1995): I test for the effect of instrument on income in subsamples where the schooling is held constant. If the instruments are valid, they should have no predictive power on income after controlling for x . The tests for the joint significance of instruments are implemented separately for each schooling category and both sexes and reported in Table 3.6. The instrument is found to have a direct effect on earnings in comprehensive schooling category for men and in the secondary education category for women. Consequently, for other education levels, the exogenous instrument assumption is retained.²¹

To further study, to what extent the possible endogeneity of instrument drives the results, I have estimated the model without an exclusion restriction

²⁰This explanation is consistent Nybom (2014) whose results suggest a rather small effect of unobserved heterogeneity on returns to schooling in Sweden.

²¹Also the IV estimates are somewhat larger than previous estimates from Finland (Uusitalo 1999). It should, however, be noted, that the earnings measures are not entirely comparable because the measure used in this paper consists of a compilation of earnings and unemployment risks. If education increases earnings and decreases the probability of being unemployed (and increases hours worked within a year), this would lead to higher mean return to education.

relying solely on the assumed nonlinearity of the Inverse Mill's Ratios for identification. The estimation results are presented in Tables 3.7 and 3.8. The results are very similar to those reported in Tables 3.4 and 3.5. Since the two alternative specifications give very similar, and quantitatively small, estimates for the unobserved heterogeneity, it seems that the results are not driven by the choice of the instrument.

The approaches presented in this subsection do not present a conclusive test for the validity of the instrument, rather they should be seen as suggestive evidence that the possible correlation between the instruments and the unobservable element of the earnings education is not driving any of the main results.

Table 3.6: Test for the exogeneity of the instrument.

| | Men | Women |
|--------------------------|--------------------------------|-------------------------------|
| Comprehensive education | 1.67* (19, 3869) [0.04] | 0.77 (19, 2482) [0.75] |
| Secondary education | 1.399 (19, 12087) [0.11] | 1.47. (19, 9030) [0.09] |
| Lower tertiary education | 1.38 (19,4914) [0.13] | 1.30 (19, 7633) [0.18] |
| University education | 0.61 (19,2075) [0.91] | 1.09 (19, 2530) [0.36] |

F-tests for the for the joint significance of instruments in samples with the same education. P-values in brackets, degrees of freedom in parenthesis. Significance levels in all specifications: *** 0.1%, ** 1%, * 5% and . 10%.

Table 3.7: Second stage estimates (estimated without an exclusion restriction).

| Men | <i>Education categories</i> | | | |
|-------|----------------------------------|-------------------------|-----------------------|----------------------------------|
| | <i>Return to education level</i> | Corrected for selection | | <i>Selection correction term</i> |
| | Upper secondary educ. | 0.25*** (0.05) | Comprehensive educ | 0.00 (0.01) |
| | Lower tertiary educ | 0.47*** (0.05) | Upper secondary educ. | 0.00 (0.01) |
| | University | 0.73*** (0.07) | Lower tertiary educ | 0.00 (0.02) |
| | | | University | 0.03* (0.02) |
| | | | | |
| Women | <i>Education categories</i> | | | |
| | <i>Return to education level</i> | Corrected for selection | | |
| | Upper secondary educ. | 0.20*** (0.05) | Comprehensive educ | 0.00 (0.02) |
| | Lower tertiary educ | 0.39*** (0.05) | Upper secondary educ. | 0.00 (0.01) |
| | University | 0.74*** (0.06) | Lower tertiary educ | 0.00 (0.01) |
| | | | University | 0.02 (0.02) |

Notes: Estimates are based on a model without an instrument. Standard errors in parenthesis. Standard errors are based on 200 bootstrap replications. In addition to variables reported, both models include controls for location of residence, parents' education and family income, nationality, first language and year of birth, age and age squared. Significance levels in all specifications: *** 0.1%, ** 1%, * 5% and . 10%.

Table 3.8: Estimates of income variance components (estimated without an exclusion restriction).

| | Men | | | |
|---|--------------------|-----------------|-----------------|-----------------|
| | Education category | | | |
| | 1 | 2 | 3 | 4 |
| Variance of transitory shock ¹ | 0.09 (0.002) | 0.07 (0.001) | 0.07 (0.001) | 0.07 (0.002) |
| Permanent component ² | 0.17 (0.01) | 0.12 (0.01) | 0.10 (0.01) | 0.10 (0.01) |
| Effect of private information on permanent component ³ | 0.00 (0.08) | 0.00 (0.04) | 0.00 (0.04) | 0.00 (0.08) |
| Total wage uncertainty ⁴ | 0.26 (0.009) | 0.20 (0.009) | 0.17 (0.007) | 0.18 (0.009) |
| | Women | | | |
| | Education category | | | |
| | 1 | 2 | 3 | 4 |
| Variance of transitory shock ¹ | 0.07 (0.002) | 0.08 (0.001) | 0.07 (0.001) | 0.08 (0.002) |
| Permanent component ² | 0.09 (0.005) | 0.07 (0.003) | 0.04 (0.002) | 0.05 (0.005) |
| Effect of private information on permanent component ³ | 0.00 (0.08) | 0.00 (0.06) | 0.00 (0.06) | 0.00 (0.07) |
| Total wage uncertainty ⁴ | 0.17 (0.004) | 0.14 (0.003) | 0.11 (0.002) | 0.14 (0.004) |

¹ $\bar{\psi}_s^2$

² σ_s^2

³ γ_s^2

⁴ $\bar{\psi}_s^2 - \gamma_s^2 + \sigma_s^2 = \tau_s^2$

Notes: Variance component decompositions are based on Equation (3.13) estimated without an instrument. Standard errors from 200 bootstrap resamples in parenthesis. Education categories are: 1. compulsory education; 2. upper secondary education; 3. lowest tertiary education; 4. bachelor level education or higher.

3.7 Conclusions

This paper applies a simple model for identifying potential income distributions. The model is based on the residuals of the income regression equation. Variance of residuals is comprised of two components: uncertainty and unobserved heterogeneity. The uncertainty is further comprised of two components: permanent income differences and transitory shocks. Using a parametric model for selection, this paper disentangles the role of unobserved heterogeneity from permanent income differences. This paper departs from previous studies in two ways: in addition to wages, measure of income also includes transfers to people who are not working. This gives a possibility also to include the unemployed in the estimation allowing for a more complete picture of income uncertainty. Second, to facilitate understanding of differences in the earnings processes of men and women, separate models for men and women are estimated.

The results indicate that education is a good investment: in addition to having higher mean income, more educated individuals have smaller permanent income differences and face smaller transitory income shocks, even after correcting for selection. Moreover, my results indicate that men face considerably riskier income processes. For example, uncertainty for men with a basic level education is about 33% higher than that of women with a similar education. The results show that the higher male income variance is by and large driven by permanent earnings differences; no differences in unobserved heterogeneity are found. In addition, transitory shocks affect both genders and almost all education groups symmetrically. Only men in the lowest education category face larger transitory earnings shocks.

The estimates on share of unobserved heterogeneity in permanent income differences are quantitatively very small. This is a stark difference from previous studies, which mostly use data from the U.S. and find that the effect of unobserved heterogeneity may be up to 50% of permanent income differences. I argue that this result is likely driven by the choice of dependent variable or the relatively young estimation sample. Both of these factors increase the noise in the dependent variable compared to specifications typically used in studies using data from the U.S.

The estimation method applied in this paper take advantage of observed choices made by individuals to infer their information sets and, consequently, unobserved heterogeneity. A possible caveat in the analysis, is that if people

know their expected incomes, but do not act on this information, the method which is based on their observed choices necessarily understates the unobserved heterogeneity. This may be a particularly relevant concern in the case of Finland, where higher education is entirely publicly funded.

The focus of this paper has been to quantify the effect of education on earnings uncertainty but the specific channel through which education affects earnings uncertainty is somewhat unclear. A classic explanation (e.g. Willis & Rosen, 1979) is that each level of education gives access to a distinct labor market with distinct income processes. In addition, education has been shown to have a variety of other positive effects on behavior (see Grossman, 2005 for a review). For example, it leads to better health (Lleras-Muney, 2005) and reduces antisocial behavior (Lochner, 2004). Furthermore, these effects are found to be more relevant to men than to women. It is plausible, that at least a portion of the high earnings uncertainty of low educated males is attributable to these behavioral factors.

Since correcting for selection has only a small effect on the estimates of means and variances of incomes conditional on education level, it appears that, in the case of Finland, not correcting for selection has only a marginal impact on the estimated returns to education and uncertainty involved.

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Appendix: Estimating $\hat{\psi}_{st}^2$ from the residuals of the within-model

Equation (3.11):

$$(y_{it} - \bar{y}_i) = (x_{it} - \bar{x}_i) \beta - (\xi_{sit} - \bar{\xi}_{si}).$$

Assuming that observations are missing at random and that ε_{st} and ε_{st-k} are independent for all $k \neq 0$, the residual variance can be written as

$$Var(\xi_{sit} - \bar{\xi}_{si}) = W_{st} = \left(1 - \frac{2}{T}\right) \psi_{st}^2 + \frac{\Omega_{si}}{T_i^2},$$

where T_i is number of observation years of observation i and $\Omega_{si} = \sum_{t=1}^{T_i} \psi_{st}^2$. Summing both sides up over t gives

$$\sum_{t=1}^{T_i} W_{st} = \left(1 - \frac{2}{T}\right) \Omega_{si} + \frac{\Omega_{si}}{T}$$

and solving this for Ω_{si} gives

$$\Omega_{si} = \frac{\sum_{t=1}^{T_i} W_{st}}{\left(1 - \frac{1}{T}\right)}.$$

Plugging this back to the expression of $Var(\nu_{sti} - \bar{\nu}_{si})$ and solving for ψ_{st}^2 gives

$$\psi_{st}^2 = W_{st} \frac{T_i}{T_i - 2} - \frac{\Omega_{st}}{T_i (T_i - 2)}.$$

Finally, replacing T_i 's with their sample average and W_{st} with its consistent estimate gives

$$\hat{\psi}_{st}^2 = \hat{W}_{st} \frac{\bar{T}}{\bar{T} - 2} - \frac{\hat{\Omega}_s}{\bar{T} (\bar{T} - 2)},$$

where $\hat{\Omega}_s = \frac{\sum_{t=1}^{T_i} \hat{W}_{st}}{\left(1 - \frac{1}{\bar{T}}\right)}.$

Chapter 4

How Risky Is the Choice of a University Major?

Abstract

This paper estimates the monetary returns to different university majors and the risks related to them. The residuals from a Mincer-type income regression are decomposed into unobserved heterogeneity (known to the individual when making her education choice) and risk (unknown to the individual). The return and risk estimates are corrected for selection by applying the selection correction model of Lee (1983) and an instrument based on the local supply of education in different majors. The differences in risks between different majors are found to be mostly statistically insignificant but differences in returns to majors are larger and significant. Both, income uncertainty and mean returns are found to be larger for men than for women.

4.1 Introduction

Human capital assets are perhaps the most important form of investments made by individuals. In a standard human capital accumulation framework, individuals invest time (and possible tuition fees) in their education and the potential return to education materializes as higher future earnings.

Since the returns to human capital are uncertain and they are realized only several years after the choice of education is made, there is an inherent uncertainty in human capital investments. This paper studies the risk-return association of a particular type of human capital assets, namely university level degrees from different majors.

There are considerable differences in earnings of people who have graduated from different majors. For instance, the raw mean earnings of people who major in medicine are roughly 60% higher than those of arts majors. In addition, there are differences in unemployment risks and earnings variances across fields. However, it is not clear, if the differences are due to the fact that different people choose to major in different fields or differences in majors as such.¹

This paper answers two interrelated questions. First, I study how much different university majors differ in their return. In addition, I study if there are differences in the earnings uncertainty related to these majors.

Comparing monetary returns of major subjects is complicated by the fact that people self-select into their major subjects. Therefore, it remains unclear whether the earnings differences between particular fields are due to different types of education or due to differences in observable (e.g. school grades and family background) or unobservable characteristics (e.g. abilities, motivation, taste for risk) between individuals who choose different majors. This *unobserved heterogeneity* may bias estimates for mean returns to major subjects upwards or downwards.² The unobserved heterogeneity also complicates the

¹A pioneer in the literature studying the risk-return nexus of human capital investments is Palacios-Huerta (2003) who studies the risk-return trade-off in education levels and compares them to financial investments. Christiansen et al. (2007) take a similar approach, but they study majors in addition to levels. Relatedly, Hartog & Vijverberg (2007) and Diaz-Serrano et al. (2008) study the association of mean income and higher moments of the income distribution between education groups. None of these papers explicitly model selection into education.

²Willis & Rosen (1979) formulate a structural model for selection into education and study how the selection biases the estimated returns to college education. Card (2001)

estimation of variances. This is because the realized dispersion in observed earnings is a result of two distinct components: an unexpected permanent income shock and unobserved heterogeneity across workers.³

Self-selected education causes the returns to a major to differ from the return we would expect to observe if the education was randomly allocated. To understand the effect of self-selection into a major subject, I correct for selection when estimating income premia and uncertainty related to major choice using the multinomial selectivity correction of Lee (1983) and a parametric assumption on the distribution of unobservables. I model each major as a distinct "market" which gives rise to a distinct earnings process.

The measure of uncertainty in this paper is the *ex ante* variance of earnings. It is the variance of earnings that is not captured by observable characteristics or unobserved heterogeneity, which is inferred from agents' choices. I decompose the *ex ante* variance into two components: a time-invariant permanent component and a transitory component which reflects idiosyncratic shocks to their income streams.⁴ The transitory component is allowed to vary with time and with education. The unobserved heterogeneity is identified from the actual education choices made by the agent. This paper studies an unordered multinomial education choice (choice of major) rather than an ordered one (high school versus college).⁵

The model presented in this paper is estimated using Finnish registry data.

surveys problems that arise due to unobservable characteristics, which affect both selection into education and the returns to it, and discusses solutions to these problems.

³Cunha et al. (2005) and Chen (2008) model the selection into education and decompose permanent income differences within an education level into unobserved heterogeneity and uncertainty using U.S. data on levels of education. The main focus of Cunha et al. (2005) is the distribution of returns of a college education, whereas Chen (2008) studies the potential variances of different levels of education corrected for selectivity effects and makes a distinction between permanent income variance and transitory income shocks.

⁴The measure of earnings risk is rather standard in the literature, but it disregards the higher moments of the income distribution. In particular, it has been shown that gamblers may be risk-averse but skew-loving at the same time (e.g. Golec & Tamarkin 1998). Further Hartog & Vijverberg (2007) show that high variance is positively correlated with income and higher skew is negatively correlated with income when comparing different majors in their data. These are consistent with the fact that workers dislike risk but are attracted to positive skew when choosing their occupation.

⁵In a recent working paper, Reyes et al. (2013) present a model of (an unordered) university choice which features observed and unobserved heterogeneity and their effect on early career wages using Chilean data. Also Napari (2008) estimates field specific returns to higher education using Finnish data but does not model selection into majors.

An attractive feature of the Finnish tax code for the current purposes is that virtually all of the income transfers, including unemployment benefits are taxable and are therefore observed in the tax registry. Therefore, the biases inherent in survey based approaches are not an issue in the current paper.

The results of this paper also have policy relevance. The perceived riskiness of some human capital investments is a subject of an on-going debate on the financing of higher education. For example, a claim persists that certain fields of education have such an inherent risk involved that without large subsidies for schooling, no one would choose those majors. By deriving major subject specific income uncertainty measures corrected for selection, this paper provides a test for differences in riskiness of different majors.

Estimating a selection model necessitates an instrument, which affects only the probability of graduating with a degree from a given major, but does not affect potential post-graduation earnings. To construct the instrument, I take advantage of an institutional feature in Finnish tertiary education. Namely, in Finland students apply directly to a university-major combination. Universities have strict quotas for how many students they accept each year for each major. These quotas define how competitive the admission to each university-major combination is and, consequently, how difficult it is to be admitted to study a given subject in a given university. For example, since the ratio of applicants to starting places is higher in medicine in Oulu compared to medicine in Helsinki, an upper secondary school graduate in Oulu is more likely to be admitted to study and to eventually graduate from medicine compared to an upper secondary school graduate from Helsinki. Even though upper secondary school graduates from Helsinki may apply to Oulu and vice versa, this mobility incurs both monetary and psychic moving costs, which make people reluctant to move. The exclusion restriction builds on the assumption that, for a marginal student, these moving costs matter so much that they affect their tertiary education choices.

Majority of papers studying monetary return to education use either hourly wages of workers or mean incomes over a long period of time as a dependent variable. This approach disregards one of the most important source of earnings uncertainty; namely, the risk of unemployment. Instead of hourly wages, this paper studies yearly total taxable income, which, in addition to income from employment, includes unemployment benefits and other taxable transfers. This measure gives a more complete picture of the income uncertainty

related to a level of education. Using total taxable income as the measure of income also mitigates the problem of endogenous selection into employment, as people are observed even if they are not working.

I estimate separate models for men and women. In most of the comparable studies attention is limited to men, because female workforce participation in most countries has been much lower until recent years. Nonetheless, female workforce participation in Finland has been very high as early as the 1990s, which warrants doing a similar analysis also for females. Furthermore, since both female education and female workforce participation has also increased internationally, I find that calculating comparable measures for males and females is also interesting in its own right from an international perspective. In addition, I am able to test whether there are differences in the uncertainty of career paths between men and women.

As a preview of the results, I find that the differences in the returns to majors are found to be far greater than the differences in risks associated with them. Further, the proportion of unobserved heterogeneity is found to be statistically indistinguishable from zero for most majors. This, in turn, suggests that the differences in returns to majors outweigh the differences in risks associated with them.

The outline of the paper is as follows. Section 4.2 discusses data; sample construction, descriptive statistics, grouping of major subjects, the definition of concept and the instrumental variables. Section 4.3 describes the empirical model. Section 4.4 discusses the first and second stage estimates. The uncertainty estimates are presented in Section 4.5. Section 4.6 concludes the paper.

4.2 Data

4.2.1 Sample construction and observables

The data used in this paper is based on longitudinal census data collected by Statistics Finland. It contains rich information on individuals' educational attainment, income, mother tongue, and region of residence and on their parental socioeconomic status (based on the occupation of both parents) and education (highest level of education of both parents); it spans the years 1990-2006. Table 4.1 gives the descriptive statistics for the main explanatory variables.

In addition to demographic and income information, the data has been linked to matriculation examination grades for years 1990-1995. Finnish upper secondary school graduates all take part in a standardized examination, which gives students a general qualification to apply for universities and vocational colleges. The examination is centrally administered and graded according to uniform criteria across the country and the results are scaled so that they are comparable across years.

There are four compulsory exams in the matriculation examination: mother tongue, the second official language, one foreign language and either mathematics or a science and arts exam. In addition, students may take exams in other foreign languages and take both the mathematics and the science and arts option. Finally, there are two alternative versions of the mathematics exam; a basic level exam and an advanced level exam. Generally, to be accepted to study a mathematically oriented major in the university, students have to have taken the advanced level exam in mathematics.

The data used in this paper includes four measures related to the matriculation examination. I observe the average grade of all tests taken (general grade). In addition, I observe grades in mother tongue and in mathematics. Finally, there is an indicator for whether a student has taken the basic level or the advanced level exam in mathematics. The exams are graded on a scale of 0-5, where 0 indicates a failed exam.⁶

I consider the matriculation examination grades as a rather good measure for general academic ability for two reasons. First, it is a standardized test which has a central role in the university admissions, so matriculation exam is a high-stakes exam. In addition, it is taken by all upper secondary school graduates regardless of whether they are planning to apply to tertiary education or not, so the grading does not suffer from selection bias. The proportions of different degrees vary between males and females in the data. For instance, technology is clearly a male-dominated field and arts a female-dominated field.

Three notes can be already made from the descriptive data. First, the university graduates earn more than the non-graduates. Further, they have less work experience, and are more academically able as evidenced by their matriculation examination grades.

⁶The grades are given on an ordinal scale as Latin words from *improbatur* (fail; 0) to *laudatur* (excellent; 5).

4.2.2 Classification of majors

To make sure that each major cell has enough observations. I have pooled the education majors into five fairly homogenous categories. These are:

- $S = 0$; Upper secondary level education,
- $S = 1$; Arts, education and social sciences,
- $S = 2$; Law,
- $S = 3$; Business,
- $S = 4$; Engineering and natural sciences, and
- $S = 5$; Medicine and pharmacy.

Pooling the majors in the aforementioned fashion reduces the number of parameters to be estimated, and therefore reduces the complexity of the model considerably.⁷ The pooling of categories is, to some extent, arbitrary. Nonetheless, categories are homogenous with respect to their matriculation examination grades and mean incomes after graduation.⁸ Nonetheless, if there is heterogeneity within the categories, this will interfere with the uncertainty estimates. The schooling $S = 0$ is used as a reference group to which all other higher education majors are compared to.

I also do a second simplification. Namely, I restrict the return to a major to be the same across different universities. I do this because the data does not have information on the actual institution from which people have graduated but only their place of residence at the time of graduation. To control for regional earnings differences, I include dummies for the region of residence at the time of graduation in the earnings regression.

⁷I have excluded fine arts graduates from the model because of the very small sample size in those subjects.

⁸Each major category consists of several major subjects. I tested if the major subject specific means of income and matriculation examination grade variables differed from one another within each grouped major category. The null hypothesis of same means was not rejected for any of these variables within a major at 5 % risk level.

| Women | | | | | | | | |
|-------------------------------------|-----------------------------------|----------------|--|-----------------|-----------------|----------------------------|-----------------|--|
| Education | Upper sec- ondary degree | sec- school | University level Arts, education, social science | Law | Business | Engineering and science | Health | |
| Sample size | 882 | | 1481 | 100 | 306 | 511 | 314 | |
| Age and potential experience | | | | | | | | |
| Potential experience | 8.69 (4.68) | | 4.97 (3.24) | 4.69 (2.92) | 5.08 (3.19) | 4.68 (2.98) | 4.96 (3.12) | |
| Age | 28.15 (4.93) | | 31.17 (3.64) | 30.93 (3.21) | 31.06 (3.38) | 30.89 (3.45) | 31.12 (3.47) | |
| Matriculation examination grades | | | | | | | | |
| Average grade | 3.20 (1.45) | | 3.92 (1.18) | 4.46 (0.98) | 4.27 (1.11) | 4.22 (1.02) | 4.04 (1.30) | |
| Mother tongue grade | 3.56 (1.18) | | 4.12 (0.96) | 4.47 (0.66) | 4.22 (0.93) | 4.24 (0.89) | 4.18 (0.98) | |
| Proportion with advanced math grade | 0.19 (1.18) | | 0.23 (0.96) | 0.43 (0.66) | 0.45 (0.93) | 0.75 (0.89) | 0.63 (0.98) | |
| Advanced math grade | 2.76 (1.45) | | 2.89 (1.36) | 3.32 (1.18) | 3.50 (1.19) | 3.87 (1.14) | 3.69 (1.22) | |
| Basic math grade | 2.18 (1.63) | | 3.00 (1.65) | 3.47 (1.73) | 3.69 (1.54) | 3.53 (1.48) | 3.07 (1.71) | |
| Dependent variable | | | | | | | | |
| Log total yearly taxable income | 9.68 (0.69) | | 10.15 (0.45) | 10.50 (0.47) | 10.50 (0.52) | 10.35 (0.52) | 10.52 (0.51) | |

Notes: Standard deviations in parenthesis. The matriculation examination grades are converted to numbers. Potential experience, and age are measured as full years since graduation. The time-varying variables (age, experience and income) are measured at individual means. In addition to variables reported, all regression specifications include controls for first language, family socioeconomic status and parental education.

I classify people according to their tertiary degrees and exclude decisions related to post-tertiary education (for example, an engineer who has later completed a doctoral degree in the arts is classified as an engineer). Furthermore, I limit my attention to people who have either completed a university level master or a bachelor level degree or, alternatively, have not finished any post-secondary degree, who are used as comparison group. Because I only have information on completed degrees, I classify university drop-outs as upper secondary school graduates. Finally, I exclude people with a vocational tertiary education. This exclusion is done because the selection into vocational tertiary education is less standardized and consequently more difficult to measure.

4.2.3 Measure of income

I observe the individuals for the time period between the years 1990 and 2006. I limit my attention to people who had completed their secondary level education between 1990 and 1995. For the people who have a post-secondary degree, I include only the earnings observations past their graduation. Further, I exclude observations where people are classified as students, retired or outside of the workforce.

The outcome variable in income regressions is the log of total yearly taxable income which, in addition to wages, includes taxable income transfers. As a result, the observed income streams allow for spells of unemployment. This reflects the fact that the risk of unemployment constitutes a considerable part of total income uncertainty. However, if a person drops out of the workforce entirely, she only contributes to the estimation for the years for which she is part of the workforce. This income concept may introduce a problem of its own, since unemployment may be voluntary or involuntary. To separate these from one another, solely individual-year observations where the main type of activity of an individual is either working or unemployed are included in the estimation⁹. The approach chosen leaves some observations with zero income. I exclude these observations. This does not affect the main results, because the share of zero-observations is very small (less than 1% of yearly observations)¹⁰.

⁹In general, for an individual to be classified as unemployed (and be eligible for unemployment benefits), she must agree to accept a job if offered one.

¹⁰None of the results qualitatively change whether I exclude them or replace the zero observations with a small positive income value.

To ensure comparability between years, the measure of income is deflated to EUR 2006 using the Consumer Price Index.

It should already be noted that the people in the sample are, on average, rather young and at the beginning of their careers. Therefore, the earnings of individuals are observed from the beginning of their career. This may drive some of the results, but I still perceive the findings as indicative of the earnings uncertainty faced by recent university graduates.

4.2.4 Exclusion restriction

To ensure that the joint identification of schooling choice and earnings equations is not solely based on functional form assumptions, I utilize an instrument, which is assumed to monotonously affect the probability of choosing a particular major subject, but not to affect the earnings after graduation.

Since post-secondary education is state sponsored in Finland, there are no cost side instruments available. Instead, I use a proxy measure for local supply of education as an instrument. Local supply of education is measured by the ratio of annual number of starting places to applicants at region level for each major¹¹. There are some regions with more than one study program offering the same major (e.g., Finnish and Swedish language universities in Varsinais-Suomi and Uusimaa). For these regions, an average of applicants-to-places ratio weighted by the number of starting places is calculated. For the regions that do not have a university or a program in a particular major, an average of applicants-to-places ratio weighted by the distance to each university region where one can study each major is calculated. The supply is measured in the year of matriculation at region level.¹²

The admission to university is based on a combination of the matriculation examination grades and the university entrance exams. It is merit-based and objective. In particular, there is no minority support or weight for extra-curricular activities. Different majors and universities give different relative weights to different subjects in the matriculation exam. Generally, the more competitive a major is, the more weight is given to the entrance examination relative to the matriculation examination.

¹¹Finland is divided into 20 administrative regions, which are the regional cultural and administrative divisions.

¹²These data are downloaded from the KOTA database maintained by the Ministry of education: <https://kotaplus.csc.fi/> (downloaded 2013-01-08).

The supply of education may be correlated with the outcome through some other channels beside its effect on choice of majors, which would threaten the validity of the instrument. As discussed by Card (1993), this may happen because families living in university regions have different educational or social backgrounds than families living in non-university regions. I address this worry by controlling for a variety of family background variables. Card's critique is also likely less valid in the context of this paper because it seems much less likely that parental characteristics would be correlated with a supply in particular major compared to supply of general university education.

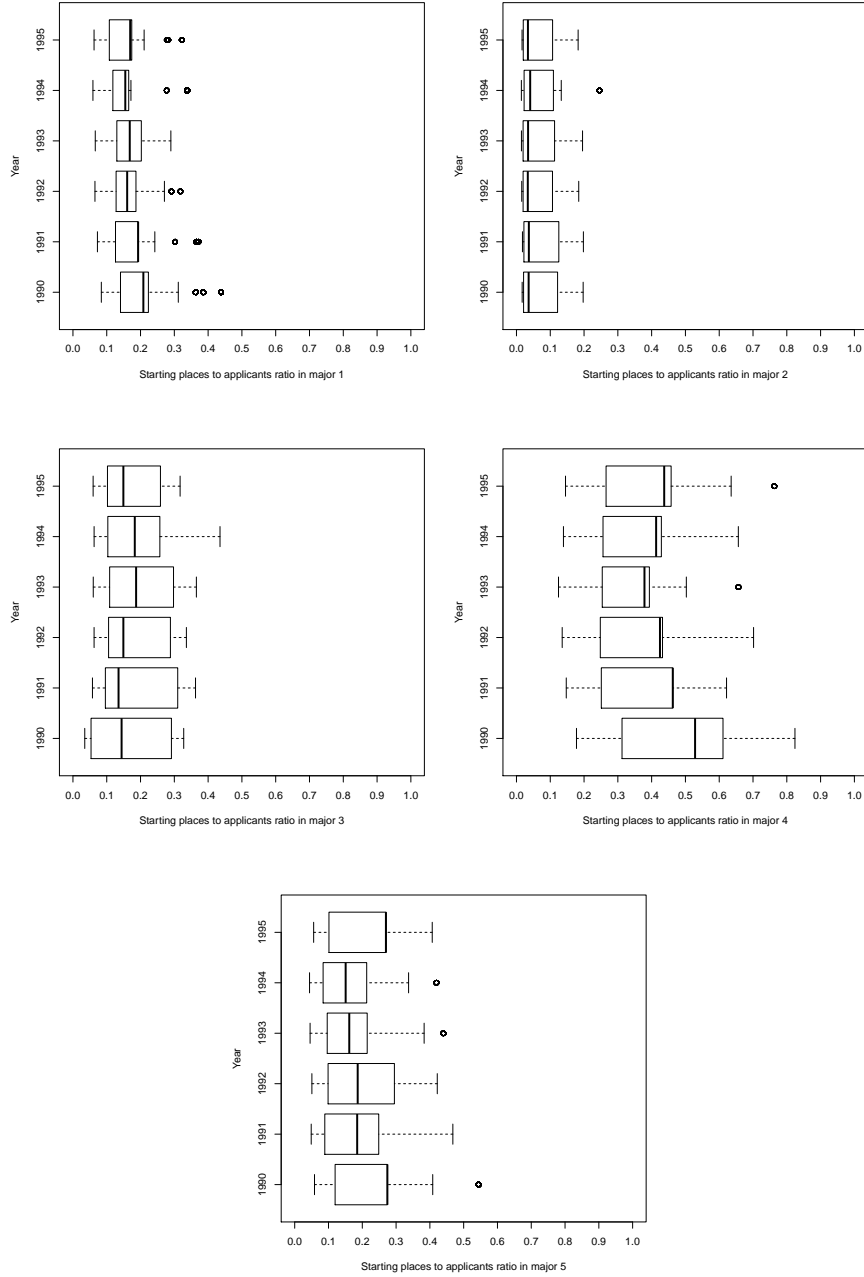
In addition, there might be differences in upper secondary school quality between regions. This might affect both the education choice and subsequent earnings of individuals, which might threaten the validity of the instrument. This is a small concern in the case of Finland because the secondary education is arranged in public schools with a standardised curriculum, very small differences in resources and quality. Furthermore, since the matriculation examination is standardized and centrally administered, it is reasonable to assume that controlling for matriculation examination grades would control also for differences in the quality of secondary education.

A third possible source of omitted variable bias is that the location of residence at the time of graduation from upper secondary school might be correlated with both the choice of university major and labour market conditions after graduating, which, in turn, would create a correlation between the instrument and the outcome. I address this concern by controlling for the region of residence at the time of graduation from upper secondary school in the earnings equation.¹³ Finally, I assume that yearly changes in starting places are so small in magnitude that they do not have any general equilibrium effects.

The instrument distributions are plotted in figure 4.1 in a box-whiskers plot for each year¹⁴. The medians are the smallest for law, and largest for science and engineering. Further, as evidenced by the interquartile ranges of the instrument, the variation between regions is largest in business and

¹³It would also be possible to include region of residence dummies from the year of observation in the outcome equation. This would increase the precision of the estimates. However, since the region of residence is determined after the choice of education has been made, it is potentially endogenous.

¹⁴In each of the plots, the strong black lines mark yearly medians for each year; boxes represent the interquartile range between 25th and 75th quantiles, and whiskers represent 1.5 times the interquartile range. Observations lying outside of the whiskers are marked as dots.



Note: The major subjects are 1: arts, education, social science; 2: Law; 3: Business; 4: Engineering and science and 5: Health.

Figure 4.1: Distribution of the instruments.

technology, and the smallest in arts. In addition, the box-and-whiskers plots reveal that for all majors there is both time and cross-sectional variation, which helps in identification of the model.

Further, for the identification of the choice model, the instruments should also have some independent variation and not simply act as proxies for living in a university region. To show that this is the case, I report the correlation matrix of instruments in Table 4.2. The correlations are considerably smaller than 1 ranging from .085 to .512 which supports the assumption that the instruments truly capture differences between university regions.

Table 4.2: Covariance matrix of starting places to applicants in fields.

| | Ratio in major 1 | Ratio in major 2 | Ratio in major 3 | Ratio in major 4 | Ratio in major 5 |
|------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Ratio in major 1 | 1 | 0.422 | 0.502 | 0.461 | 0.512 |
| Ratio in major 2 | | 1 | 0.466 | 0.085 | 0.377 |
| Ratio in major 3 | | | 1 | 0.486 | 0.298 |
| Ratio in major 4 | | | | 1 | 0.450 |
| Ratio in major 5 | | | | | 1 |

Notes: Ratio is calculated as starting places divided by number of applicants to each major. The major subjects are 1: arts, education, social science; 2: Law; 3: Business; 4: Engineering and science and 5: Health.

4.3 Empirical model

In this section, I present the selection correction methodology of Lee (1983) applied to the context of major choices.

4.3.1 Selecting into major and income processes

The model features an unordered schooling decision. Conditional on observed and unobserved characteristics, agents make their major choice based on the comparison of the expected utility associated with each major subject. This utility includes both monetary and non-monetary benefits as well as monetary and psychic costs. I assume that the earnings processes of individuals are determined by the agent's observed and unobserved characteristics plus a permanent earnings shock and a yearly transitory shock, both of which may depend on the choice of education made by the agent. In essence, I allow for observationally similar individuals to have different realizations for the return to completing a degree. I interpret the variance of these returns as uncertainty related to the choice of education.

The stylized model consists of two stages. In stage one, each high school graduate chooses their preferred major subject or, alternatively, enters the labour market with a high school education. In the second stage, university graduates enter the labour market and face income streams which are determined by major specific mean incomes, permanent earnings differences and transitory shocks. There are N individuals who are observed over T periods and have to make their education choice over alternatives $S_i = 0, 1, \dots, M$. The log total income of individual i with education s in year t is given by

$$y_{sti} = \alpha_s + x_{ti}\beta + \sigma_s e_{si} + \psi_{st}\varepsilon_{sti}, \quad (4.1)$$

where α_s is a major specific intercept and x_{it} is a vector of observables. x_{it} is a vector of control variables, which includes year of birth, parental education, socioeconomic status, mother tongue dummies, and matriculation examination grades from mathematics, mother tongue, the mean of all examination grades and a dummy variable which indicates whether the students have completed a basic or an advanced syllabus in mathematics. In addition, I include a measure for potential experience and its square. It is calculated as the difference of the observation year and the year of graduation.

The error term of (4.1) consists of two uncorrelated standard normal components, with

$$\begin{bmatrix} e_{si} \\ \varepsilon_{sti} \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right).$$

The variances of two independent shocks are scaled by σ_s and ψ_{st} .

e_{si} captures the time-invariant earnings potential for major s . $\sigma_s e_{si}$ are allowed to be correlated with the observable characteristics x_{it} . The term ε_{sti} , on the other hand, captures the transitory income shocks, which are assumed to be uncorrelated with the other terms in (4.1).

The potential problem of selection arises because agents' major choices and their earnings potential in the major might be correlated with one another. I formalize the selection into education as a multinomial selection model of Lee (1983). Denote the utility individual i from choice s as

$$V_{si} = z_{si}\gamma_s + \eta_{si},$$

where the vector $z_i = (z_{1i}, \dots, z_{Mi})$ includes all time-invariant components of x_i , and a major-specific instrument which is assumed to only affect the

choice of major, but not the monetary returns of graduating from a major. I assume that the error terms η_{si} in the utility functions are identically and independently Gumbel distributed, and independent of z_{si} . The error terms η_s capture the private information related to agents' major choice, such as motivation, tastes, and the unobserved ability.

Agents choose major s if and only if

$$V_{si} > V_{ji}, \forall j \neq s,$$

which is equivalent to

$$\begin{aligned} z_{si}\gamma_s + \eta_s &> z_{ji}\gamma_j + \eta_j, \forall j \neq s \\ \Leftrightarrow \max_j \{z_{ji}\gamma_j - z_{si}\gamma_s + \eta_s - \eta_j\} &< 0, \forall j \neq s \\ \Leftrightarrow \nu_{si} &< \Phi^{-1}(P_{Si}), \end{aligned}$$

where $\nu_{si} \sim N(0, 1)$, and

$$P_{Si} = P(S_i = s | z_i) = \frac{\exp(z_{si}\gamma_s)}{\sum_{j=1}^M \exp(z_{ji}\gamma_j)}. \quad (4.2)$$

It is further assumed that the joint distribution of the transformed variable ν_{si} and e_{si} is bivariate standard normal with a correlation coefficient ρ_s . Now the analysis of Heckman (1979) (which relies on the joint normality of error terms) can be applied to the transformed random variable ν_{si} .

Under these assumptions, the expected earnings of an individual who has chosen s , read as

$$\begin{aligned} E[y_{sti} | S_i = s, x_{ti}, z_{ti}] &= E[y_{sti} | z_{si}\gamma_s > \nu_{si}, x_{ti}, z_{ti}] \\ &= \alpha_s + x_{ti}\beta - \sigma_s \rho_s \lambda_s(z_i), \end{aligned} \quad (4.3)$$

$$= \alpha_s + x_{ti}\beta - \mu_s \lambda_s(z_s), \quad (4.4)$$

where

$$\lambda_s(z_i) = \frac{\phi(\Phi^{-1}(P_{Si}))}{P_{Si}},$$

and $\mu_s = \sigma_s \rho_s$.

Selection also implies that the observed earnings distribution is truncated, and its variance reads as:

$$\begin{aligned} Var[y_{sti} | S_i = s, x_{ti}, z_{ti}] &= Var[\sigma_s e_{si} + \psi_{st} \varepsilon_{sti} | z_{si}\gamma_s > \nu_{si}, x_{ti}, z_{ti}] \\ &= \sigma_s^2(1 - \rho_s^2 \delta_{si}) + \psi_{st}^2, \end{aligned} \quad (4.5)$$

where

$$\delta_{si} = (\Phi^{-1}(P_{si}) + \lambda_s(z_i)) \lambda_s(z_i)$$

gives the degree of understatement of the observed earnings variance compared to potential earnings variance, which would be observed if the education was randomly assigned¹⁵.

Equation (4.3) captures the observed earnings given that agents have chosen s . In particular, it demonstrates, that if $\mu_s \neq 0$, not correcting for selection will give biased estimates for the returns to each major.

$$\tau_{st} = Var(\sigma_s e_{si} + \psi_{st} \varepsilon_{sti} \mid \eta_{0i}, \dots, \eta_{Si}, x_{ti}, z_i) = \sigma_s^2 (1 - \rho_s^2) + \psi_{st}^2 \quad (4.6)$$

is the unforeseeable component of the earnings residual, or earnings uncertainty, which is corrected for selection and truncation.

The uncertainty related for each major in expression(4.6) consists of two parts. The first term is the permanent component net of unobserved heterogeneity, and the second component is the yearly-varying transitory shock. Equation (4.6) also directly implies that whenever $\rho_s \neq 0$, observed earnings inequality is smaller than the potential earnings inequality, which we would observe if the major subjects were randomly assigned.

Further, it is worth noting, that the difference between expressions (4.5) and (4.6) is that (4.5) captures the observed variance of earnings conditional on observables, and (4.6) captures the potential variance, which we would observe major subjects were randomly assigned.

4.3.2 Identification of variance components

Equations (4.3), and (4.5) suggest a step-wise approach for identifying the components of (4.6). First, selection equation (4.2) is estimated by maximum likelihood. Thereafter, the terms $\hat{\lambda}_{si}$ and $\hat{\delta}_{si}$ are estimated. In the second step, a within-individual model

$$y_{sti} - \bar{y}_{si} = (x_{ti} - \bar{x}_{si}) \beta + (\vartheta_{sti} - \bar{\vartheta}_{si}), \quad (4.7)$$

where $\vartheta_{sti} = \psi_{st} \varepsilon_{sti}$, and \bar{y}_{si} , \bar{x}_{si} and $\bar{\vartheta}_{si}$ denote individual means of the corresponding variables, is estimated. Note that the selection bias terms λ_s

¹⁵The expressions for δ_{si} and λ_{si} are derived in Bourguignon et al. (2007).

are time-invariant, so they are incorporated in the fixed effects. Term ψ_{st}^2 can be solved from the variance of the residual terms (See Appendix for derivation).

Parameters $\hat{\alpha}_s$, $\hat{\beta}$, and $\hat{\mu}_s$ can be estimated from the between-individuals model.

$$\bar{y}_{si} = \alpha_s + \bar{x}\beta + \mu_s\lambda_{si} + w_i. \quad (4.8)$$

Residual term in (4.8) equals

$$w_i = \sigma_s e_{si} + \bar{\vartheta}_{si} - \mu_s \lambda_{si},$$

and by the inclusion of $\mu_s \lambda_{si}$ into (4.8) its expectation is zero, which also ensures that the estimate for α_s is unbiased.

Variance of w_i reads as

$$Var[w_i | S_i = s, \bar{x}_{ti}, z_i] = \sigma_s^2 e_{si} - \mu_s^2 \delta_{si} + \frac{\sum_t \psi_{st}^2}{T}.$$

Replacing each parameter with their consistent estimate, and solving for $\hat{\sigma}_s$, gives a consistent estimate for the permanent earnings variance.

$$\hat{\sigma}_s^2 = \hat{Var}[w_i | S_i = s, \bar{x}_{ti}, z_i] + \mu_s^2 \hat{\delta}_s - \hat{\psi}_s^2.$$

Each term in (4.6) is now identified:

$$\hat{\tau}_{st}^2 = \hat{\sigma}_s^2 - \hat{\mu}_s^2 + \hat{\psi}_{st}^2.$$

4.4 Estimation results

4.4.1 First stage

The first stage of the model is estimated by a maximum likelihood multinomial logit. Each of the multinomial logit models includes the following background variables: gender, year of birth, parental education, socioeconomic status and mother tongue dummies. Academic ability of individuals is measured by matriculation examination grades from mathematics, mother tongue, the mean of all examination grades and a dummy which indicates whether students have completed a basic or an advanced syllabus in mathematics. In addition, the selection model includes the instrument, which is the ratio of starting places to applicants for each of the major choices. I estimate separate selection models for men and women.

Since the applicants-to-places ratio varies in time and across majors, the data would also allow me to estimate a more flexible model where the effect of applicants-to-places ratio would vary across major choices. Because of small sample sizes in some majors, the coefficient on the ratio is indistinguishable from the model where the coefficient of the ratios are restricted to be identical between majors. I have therefore opted to use a simpler model where major dummies are not interacted with applicants-to-places ratio, and is therefore constant between majors.

The parameter estimates are reported in Table 4.3. Association between the probability of graduating from arts and the grade in mother tongue are positively associated with one another at conventional statistical significance levels. Scoring high in the mathematics exam is associated with the probability of graduating from medicine and engineering, and the general grade is statistically significantly positively associated with the probability of graduating from business, arts, and law.

To facilitate the interpretation of the impact of the instrument on selection, Table 4.4 reports the marginal effect of the places-to-applicants ratio on the selection into different majors. The marginal effects are evaluated at major means. A ten percent increase in the applicants-to-places ratio implies an increase for the probability of graduating from a major between 13 percentage (for engineering) and 2 percentage (for medicine) for men. The corresponding marginal effects range between 24 percentage (for arts) and 2.7 percentage (for law) for women.¹⁶

¹⁶It should be noted that since the coefficient on the instrument is restricted to be the same across major choices, the variation shown in Table 4.3 is solely driven by the variation in baseline probabilities of graduating from different majors.

Table 4.3: Multinomial logit estimates of major choice

| | Men | Women |
|--|---------------------|---------------------|
| General grade \times Arts | 0.322*** (0.065) | 0.178*** (0.047) |
| Mother tongue grade \times Arts | 0.285*** (0.066) | 0.294*** (0.056) |
| Advanced level exam in math \times Arts | 0.426* (0.217) | 0.637** (0.228) |
| Math grade \times Arts | 0.03 (0.043) | 0.217*** (0.029) |
| Advanced level exam in math \times math grade \times Law | -0.34 (0.061) | -0.075 (0.071) |
| General grade \times Law | 0.962*** (0.191) | 0.563*** (0.177) |
| Mother tongue grade \times Law | 0.065 (0.161) | 0.366*** (0.174) |
| Advanced level exam in math \times Law | -0.042 (0.593) | 1.495** (0.522) |
| Math grade \times Law | 0.010 (0.089) | 0.292*** (0.072) |
| Advanced level exam in math \times math grade \times Law | -0.182 (0.146) | -0.027 (0.140) |
| General grade \times Business | 0.449*** (0.096) | 0.369*** (0.098) |
| Mother tongue grade \times Business | -0.017 (0.088) | 0.089 (0.099) |
| Advanced level exam in math \times Business | 0.312 (0.320) | 1.505*** (0.364) |
| Math grade \times Business | 0.152** (0.062) | 0.508*** (0.052) |
| Advanced level exam in math \times math grade \times Business | 0.022 (0.078) | 0.223*** (0.097) |
| General grade \times Engineering | 0.043 (0.064) | 0.003 (0.081) |
| Mother tongue grade \times Engineering | -0.021 (0.058) | 0.112 (0.086) |
| Advanced level exam in math \times Engineering | 0.279 (0.251) | 1.262*** (0.315) |
| Math grade \times Engineering | 0.145** (0.066) | 0.467*** (0.056) |
| Advanced level exam in math \times math grade \times Engineering | 0.632*** (0.053) | 0.641*** (0.081) |
| General grade \times Medicine | 0.294* (0.146) | -0.021 (0.083) |
| Mother tongue grade \times Medicine | 0.300** (0.136) | 0.222* (0.092) |
| Advanced level exam in math \times Medicine | 0.407 (0.576) | 1.067*** (0.336) |
| Math grade \times Medicine | 0.226 (0.121) | 0.332*** (0.058) |
| Advanced level exam in math \times math grade \times Medicine | 0.309** (0.115) | 0.469*** (0.089) |
| Ratio | 0.609** (0.287) | 1.00*** (0.290) |

Notes: Omitted category is upper secondary school. Ratio is calculated as starting places divided by number of applicants to each major. In addition to the variables reported, both models include controls for regression specifications include controls for year of birth, first language, family socioeconomic status and parental education dummies. Significance levels in both models: *** 0.1%, ** 1%, * 5% and . 10%.

Table 4.4: Marginal effects of the instrument.

| | Men | Women |
|-------------|--------------------|---------------------|
| Arts | 0.081** (0.038) | 0.242*** (0.070) |
| Law | 0.015** (0.007) | 0.027*** (0.008) |
| Business | 0.046** (0.022) | 0.077*** (0.022) |
| Engineering | 0.13** (0.061) | 0.118*** (0.034) |
| Medicine | 0.021** (0.010) | 0.081*** (0.024) |

Notes: Marginal effects evaluated at means of each major. Significance levels in both models: *** 0.1%, ** 1%, * 5% and . 10%.

4.4.2 Return to major estimates

I present the estimates based on the between individuals regression model (Equation (4.8)) in this subsection. The results are given in Table 4.5.

Adding the estimated λ_s 's as regressors gives unbiased estimates for the return to education estimates, but the estimated covariance matrix of the estimates is biased because it disregards the sampling error in the generated regressors. To correct for the extra sampling variability, I have resorted to a block bootstrap procedure where 250 samples of size N are drawn with replacement from the original population. For each bootstrap draw k , the estimates $\hat{\alpha}_s^k, \hat{\beta}^k$ and $\hat{\mu}_s^k$ are calculated. Expected values and standard errors of the parameters are calculated from the distribution of these bootstrap draws.

The first column of Table 4.5 reports the return estimates calculated from a model without any controls. Second column in Table 4.5 reports the return estimates with after controlling for x , and the third column reports the return estimates controlling for x , and λ_s . Comparing the return estimates of the first and the second and third column reveals that controlling for family background, matriculation examination grades and potential experience increases the return estimates considerably. The effect of selection correction is much smaller.

The Wald test for the joint significance of the correction function terms can be interpreted as a test for the significance of the unobserved heterogeneity over the entire sample. The p-value of 0.15 for suggests that the impact of unobserved heterogeneity is rather inaccurately estimated in the male sample. The corresponding value of $p=0.08$ for women is borderline significant.

Selection correction increases the return estimates for all majors, but the differences of corrected and uncorrected estimates are not statistically significant, as evidenced by the Hausman test statistics reported in Table 4.5. This is driven by the fact that selection correction inflates the standard errors of the return estimates.

If the selection correction terms were not statistically significant, both OLS and the selection corrected models would be unbiased, but OLS is more efficient. Under the alternative hypothesis, OLS is biased, but the selection corrected estimates are unbiased. The Wald test statistics reported in Table 4.5 are insignificant for males, and weakly significant for females.

There are considerable differences in the returns to majors.¹⁷ For both sexes, the largest corrected return estimates are for health (169 log points for men, and 129 log points for women). The smallest corrected return estimates are for the arts degree, which are 104 log points for men, and 92 log points for men.¹⁸ The return estimates are larger and earnings profiles steeper for males than for females. A potential explanation for this is that fertility decisions of women in their late 20s and early 30s cause longer breaks in their careers than they do for men (see, e.g., Lundberg & Rose 2000).

4.4.3 Uncertainty estimates

This subsection discusses the uncertainty estimates related to each of the majors. The uncertainty is defined as the ex ante variance of earnings not captured by the observable characteristics or the correction function. Uncertainty is further decomposed into two orthogonal components: permanent earnings inequality and transitory shocks. The uncertainty estimates are presented in Table 4.6.

I start by discussing the variance of transitory shocks which are reported in the first row of Tables 4.6 A and B. Since the transitory shocks are time-varying, I concentrate first on their time means. Comparing the leftmost column in Tables 4.6 A and B to the others reveals that completing a university

¹⁷ Differences are significant at $p < 0.05$ significance level for both sexes and uncorrected and corrected specifications.

¹⁸ Though not discussed in detail, I have also experimented with a specification where the potential experience terms are interacted with the major dummies to allow the income trajectories vary between majors. I find that the interaction terms do not jointly statistically significantly differ from one another, but the returns to major estimates are unrealistically large.

Table 4.5: Estimated earnings equation.

| | Men | | Women | |
|---|---------------------|----------------------|---------------------|---------------------|
| | No controls | Corrected | No controls | Corrected |
| (Intercept) | 9.765*** (0.016) | 9.416*** (0.477) | 9.518*** (0.015) | 8.709*** (0.841) |
| Arts, education, and social sciences | 0.596*** (0.030) | 0.987*** (0.048) | 0.606*** (0.020) | 0.815*** (0.036) |
| Law | 0.867*** (0.063) | 1.205*** (0.071) | 0.930*** (0.049) | 1.108*** (0.059) |
| Business | 0.987*** (0.038) | 1.323*** (0.053) | 0.956*** (0.030) | 1.124*** (0.043) |
| Engineering and technology | 0.844*** (0.024) | 1.181*** (0.046) | 0.758*** (0.026) | 0.912*** (0.039) |
| Medicine | 1.263*** (0.055) | 1.561*** (0.066) | 1.010*** (0.030) | 1.176*** (0.041) |
| Experience | | 0.117*** (0.015) | | 0.011 (0.014) |
| Experience ² | | -0.003*** (0.001) | | 0.002* (0.001) |
| General grade | | -0.017 (0.012) | | -0.017 (0.009) |
| Advanced level exam in math | | 0.031 (0.042) | | 0.017 (0.038) |
| Mother tongue grade | | -0.002 (0.011) | | 0.014 (0.01) |
| Math grade | | 0.029*** (0.009) | | 0.023*** (0.005) |
| Math grade × advanced exam | | 0.042*** (0.011) | | 0.037*** (0.01) |
| μ_0 | | | | 0.037 (0.013) |
| μ_1 | | | | 0.054 (0.054) |
| μ_2 | | | | -0.077 (0.06) |
| μ_3 | | | | 0.011 (0.129) |
| μ_4 | | | | -0.059 (0.075) |
| μ_5 | | | | -0.103* (0.053) |
| | | | | -0.045 (0.045) |
| Wald test for joint sig- nificance of correction function (df=6) | - | 9.37 [0.15] | - | 10.53 [0.08] |
| Hausman test for dif- ference between uncor- rected and corrected returns to education (df=5) | | 9.03 [0.11] | | 7.43 [0.20] |

Notes: Standard errors in parenthesis; p-values in brackets. Standard errors are calculated by bootstrap. The matriculation examination grades are converted to numbers. Potential experience is measured as full years since graduation. In addition to variables reported, uncorrected and corrected regression specifications include controls for year of birth, first language, family socioeconomic status, parental education and dummies for region of residence at the time of graduation. Significance levels in all specifications: *** 0.1%, ** 1%, * 5% and . 10%.

degree decreases transitory uncertainty considerably. The decrease is almost four-fold for men and over two-fold for women. The differences between majors are rather small and do not differ from one another at conventional risk levels.

Yearly transitory shock variances are plotted in Figure 4.2. The yearly transitory shocks are particularly large for the year 1993. This is likely explained by the exceptionally deep recession which took place in Finland in the early 1990's. Further, the sample sizes for the years in the start of the sample are very small.

Second rows in Tables 4.6 A and B report permanent earnings differences. People with a university education face somewhat larger permanent earnings differences compared to upper secondary school graduates, but the smaller transitory shocks of the university graduates compensates for the increase in permanent earnings differences. In total, university graduates face smaller earnings uncertainty than upper secondary school graduates.

Among male university graduates, engineering graduates face 30 % smaller permanent earnings differences in comparison to other major groups' average ($p = 0.05$). Among female graduates, no statistically significant differences emerge.

Permanent earnings shocks are further decomposed into two parts: permanent earnings uncertainty and unobserved heterogeneity. Unobserved heterogeneity is reported in row three of Tables 4.6 A and B. The estimates for unobserved heterogeneity are inaccurately estimated and small – and nondiscernible from zero at conventional significance levels. Shares of unobserved heterogeneity in total uncertainty are visualized in Figure 4.3.

Transitory effect dominates permanent earnings differences for both genders and all education groups. This observation may be driven by the fact that people in the data are in the beginning of their careers. Young people are more likely to be engaged in job shopping and are less likely to be protected by tenure. The finding that younger workers face larger transitory shocks than older ones is a common finding from several developed countries. Nonetheless, it is often the case that early career earnings shocks tend to evolve into permanent earnings differences as people gather more work experience and are able to secure their employment (see e.g., Baker & Solon, 2003).

Key empirical findings of this section are four. First, completing an university degree decreases uncertainty regardless of major and gender. Second, no differences between majors arise, with the exception of males who have

graduated from engineering. Third, the impact unobserved heterogeneity is estimated to be economically small and statistically insignificant. Fourth, men face larger income uncertainty than women.

Table 4.6: Uncertainty estimates

| | A | Men | University level | | | Law | Business | Engineering and science | Health |
|--|---|---------------------|------------------------|---------------------|---------------------------------|---------------------|---------------------|-------------------------|--------|
| | | | Upper secondary degree | sec-school | Arts, education, social science | | | | |
| Transitory shocks ¹ | | 0.392*** (0.024) | 0.097*** (0.014) | 0.112*** (0.023) | 0.153*** (0.030) | 0.128*** (0.016) | 0.114*** (0.016) | | |
| | | 0.031 (0.038) | 0.086*** (0.024) | 0.109** (0.059) | 0.101** (0.048) | 0.035* (0.018) | 0.137*** (0.036) | | |
| Permanent earnings variance ² | | 0.022 (0.019) | 0.007 (0.01) | 0.017 (0.026) | 0.014 (0.021) | 0.016 (0.012) | 0.009 (0.015) | | |
| | | 0.423*** (0.031) | 0.187*** (0.022) | 0.217*** (0.06) | 0.162*** (0.047) | 0.257*** (0.012) | 0.246*** (0.036) | | |
| B | | | | | | | | | |
| Women | | | | | | | | | |
| Transitory shocks ¹ | | 0.216*** (0.013) | 0.095*** (0.01) | 0.103*** (0.019) | 0.104*** (0.013) | 0.119*** (0.018) | 0.133*** (0.028) | | |
| | | 0.057** (0.022) | 0.068*** (0.015) | 0.064 (0.072) | 0.037* (0.020) | 0.063*** (0.019) | 0.042*** (0.029) | | |
| Permanent earnings variance ² | | 0.004 (0.006) | 0.010 (0.011) | 0.017 (0.022) | 0.009 (0.013) | 0.013* (0.007) | 0.013* (0.006) | | |
| | | 0.269*** (0.020) | 0.153*** (0.016) | 0.150*** (0.068) | 0.132*** (0.020) | 0.169*** (0.020) | 0.171*** (0.024) | | |
| Total uncertainty ⁴ | | | | | | | | | |

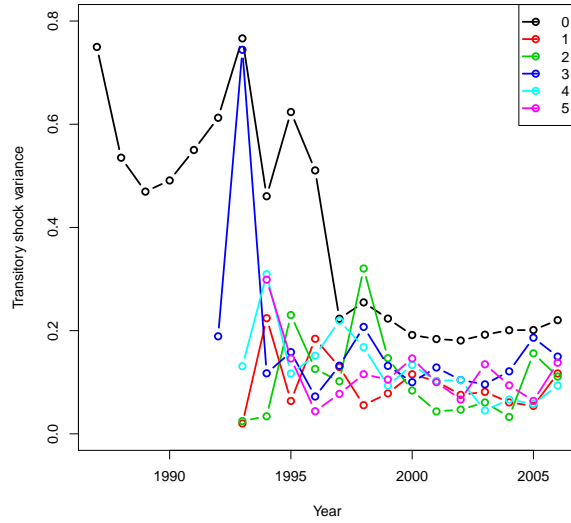
¹ Given by $\frac{\psi_{st}^2}{T}$

² Given by σ_s^2

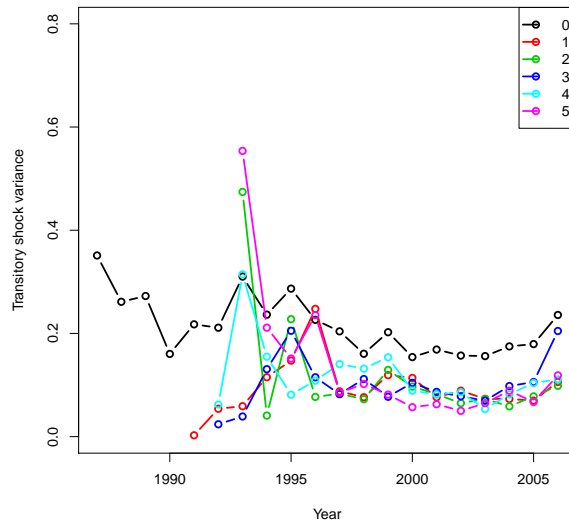
³ Given by μ_s^2

⁴ Given by $\sigma_s^2 - \mu_s^2 + \frac{\psi_{st}^2}{T}$

Notes: Bootstrapped standard errors in parentheses. Estimates refer to elements of Equation (4.11). Significance levels in all specifications: *** 0.1 %, ** 1%, * 5% and . 10%.



(a) Men



(b) Women

Figure 4.2: Yearly transitory shock variances by education categories. Majors are classified as follows: 0: Upper secondary school graduate; 1: Arts, education, social science; 2: Law; 3: Business; 4: Engineering and science and 5: Health.

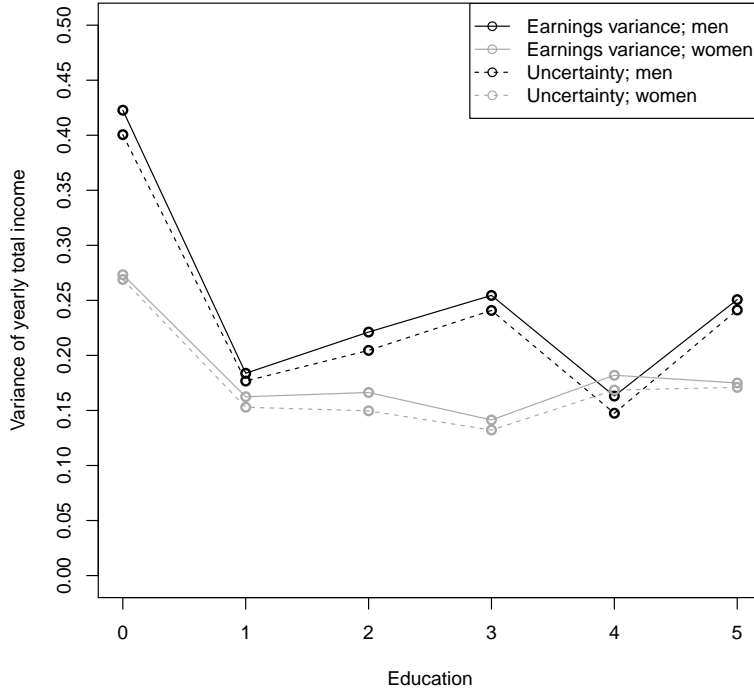


Figure 4.3: The solid lines represent the total observed earnings variances for men (black) and women (gray). The dashed lines represent the estimated uncertainty. Education category 0 refers to no university education, and categories 1–5 refer to university majors. The majors are classified as follows: 1: Arts, education, social science; 2: Law; 3: Business; 4: Engineering and science and 5: Health.

4.5 Conclusions

This paper studies returns to university majors, and the uncertainty related to them in the presence of selection bias and unobserved heterogeneity. Using this model, residuals of an earnings regression are decomposed into two types of earnings shocks: permanent earnings differences, and a yearly transitory earnings shocks; and to an unobserved heterogeneity component, which is known to the agent, but unobservable to the researcher. In addition to

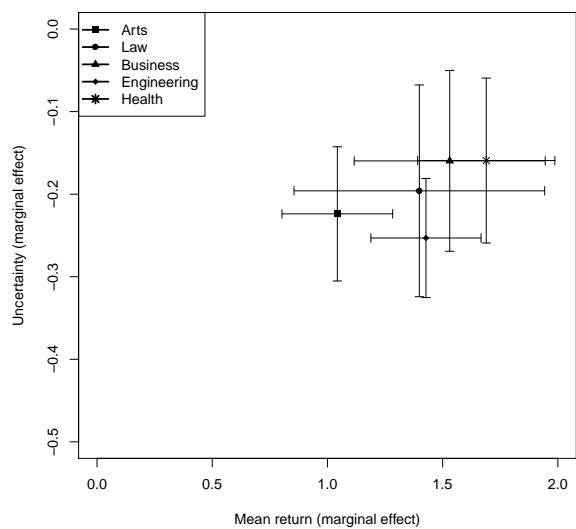
wages, measure of income used in this study includes transfers to people who are not working. This gives a possibility also to include the unemployed in the estimation allowing for a more complete picture of income uncertainty.

University majors are aggregated into five roughly similar categories. Local differences in the supply of education measured by the starting places to applicants ratio are used as instruments for selection into majors. Possible bias due to self-selection is controlled by applying a multinomial selection correction model of Lee (1983), and an instrument based on local variation in the selectivity of different majors.

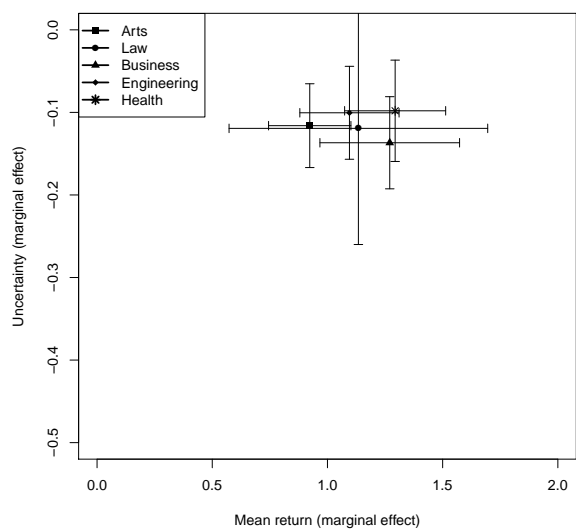
Substantive results of this paper are summarized in Figure 4.4. The effect of completing an academic degree ranges between 104 and 169 for men and between 92 and 129 log points for women over the earnings of an upper secondary education. In addition to increasing expected returns, university education also is found to decrease earnings uncertainty for both sexes. The differences in the earnings uncertainty are found to be statistically significant at 5% risk level, whereas the confidence intervals for the uncertainty estimates of different majors overlap making them statistically indistinguishable from one another.

Selection correction terms do not enter statistically significantly to either of the models, which implies that the corrected and uncorrected returns estimates are statistically indistinguishable from one another, and that the estimate for the unobserved heterogeneity is very close to zero. This is likely partly due to the small sample sizes in many of the majors, and broad set of control variables utilised.

Notwithstanding the caveats related to small sample sizes, this paper contributes another piece of evidence suggesting that (higher) education is a good investment from the point of view of the individual. In addition to increasing expected earnings, graduating from a university decreases earnings uncertainty. This notion holds regardless of the major subject.



(a) Men



(b) Women

Figure 4.4: Mean-variance plots. Notes: vertical and horizontal lines represent 95% confidence intervals for estimates.

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Appendix: Estimating $\hat{\psi}_{st}^2$ from the residuals of the within-model

Equation 4.7:

$$y_{sti} - \bar{y}_{si} = (x_{ti} - \bar{x}_i) \beta + (\vartheta_{sti} - \bar{\vartheta}_{si})$$

Assuming that observations are missing at random and that ε_{st} and ε_{st-k} are independent for all $k \neq 0$, the residual variance can be written as

$$Var(\vartheta_{sti} - \bar{\vartheta}_{si}) = W_{st} = \left(1 - \frac{2}{T}\right) \psi_{st}^2 + \frac{\Omega_{si}}{T_i^2},$$

where T_i is number of observation years of observation i and $\Omega_{si} = \sum_{t=1}^{T_i} \psi_{st}^2$. Summing both sides up over t gives

$$\sum_{t=1}^{T_i} W_{st} = \left(1 - \frac{2}{T}\right) \Omega_{si} + \frac{\Omega_{si}}{T}$$

and solving this for Ω_{si} gives

$$\Omega_{si} = \frac{\sum_{t=1}^{T_i} W_{st}}{\left(1 - \frac{1}{T}\right)}.$$

Plugging this back to the expression of $Var(\vartheta_{sti} - \bar{\vartheta}_{si})$ and solving for ψ_{st}^2 gives

$$\psi_{st}^2 = W_{st} \frac{T_i}{T_i - 2} - \frac{\Omega_{st}}{T_i (T_i - 2)}.$$

Finally, replacing T_i 's their sample average and W_{st} with its consistent estimate gives

$$\hat{\psi}_{st}^2 = \hat{W}_{st} \frac{\bar{T}}{\bar{T} - 2} - \frac{\hat{\Omega}_s}{\bar{T} (\bar{T} - 2)},$$

where $\hat{\Omega}_s = \frac{\sum_{t=1}^{T_i} \hat{W}_{st}}{\left(1 - \frac{1}{\bar{T}}\right)}.$